# CS540 Introduction to Artificial Intelligence

## (Deep) Neural Networks Summary

Josiah Hanna
University of Wisconsin-Madison

**November 9, 2021**

Slides created by Sharon Li [modified by Josiah Hanna]

# Announcements

1. Midterm released; let me know by Thursday if you have questions on your grade.

2. Homeworks 1-5 grades; regrades in progress.

| | | | |
|---|---|---|---|
| Tuesday, Nov 9 | Review and discussion on Neural Networks and Deep Learning | | |
| Thursday, Nov 11 | Search I: Un-Informed search | | |
| Tuesday, Nov 16 | Search II: Informed search | | HW7 Due; HW8 Released |
| Thursday, Nov 18 | Advanced Search and Review on Search | | |
| **Everything below here is tentative and subject to change.** | | | |
| Tuesday, Nov 23 | Games - Part I | | HW8 Due; HW9 Released |
| Thursday, Nov 25 | Happy Thanksgiving! (No class) | | |
| Tuesday, Nov 30 | Games - Part II | | |
| Thursday, Dec 2 | Reinforcement Learning I | | HW9 Due; HW10 Released |
| Tuesday, Dec 7 | Reinforcement Learning II | | |
| Thursday, Dec 9 | Review on Games and Reinforcement Learning | | |
| Tuesday, Dec 14 | Ethics and Trust in AI | | HW10 Due |

# How to classify

**Cats vs. dogs?**

# How to classify

**Cats vs. dogs?**

Single-layer Perceptron

↓

Multi-layer Perceptron

↓

Training of neural networks

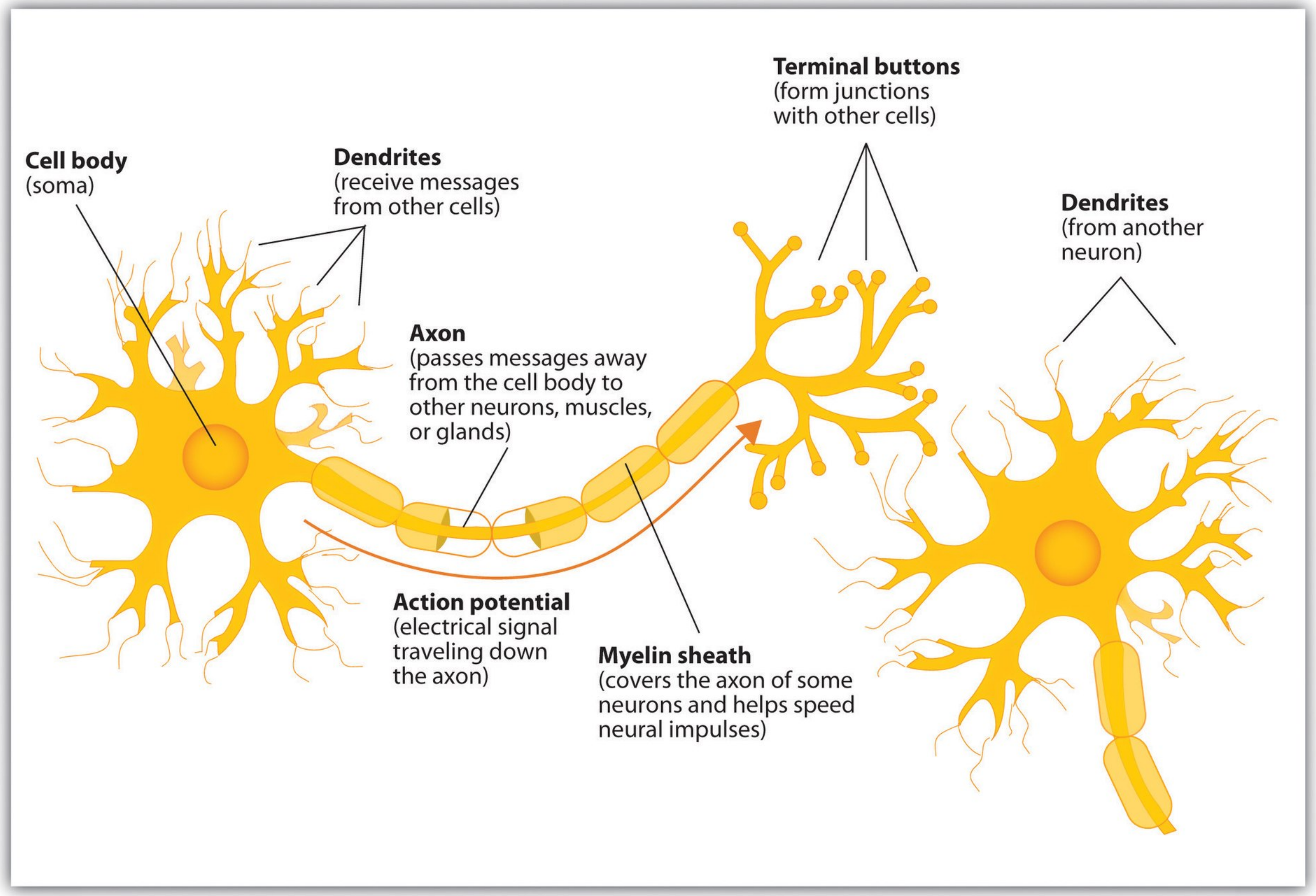
↓

Convolutional neural networks

# Inspiration from neuroscience

- Inspirations from human brains
- Networks of simple and homogenous units (a.k.a **neuron**)

(wikipedia)

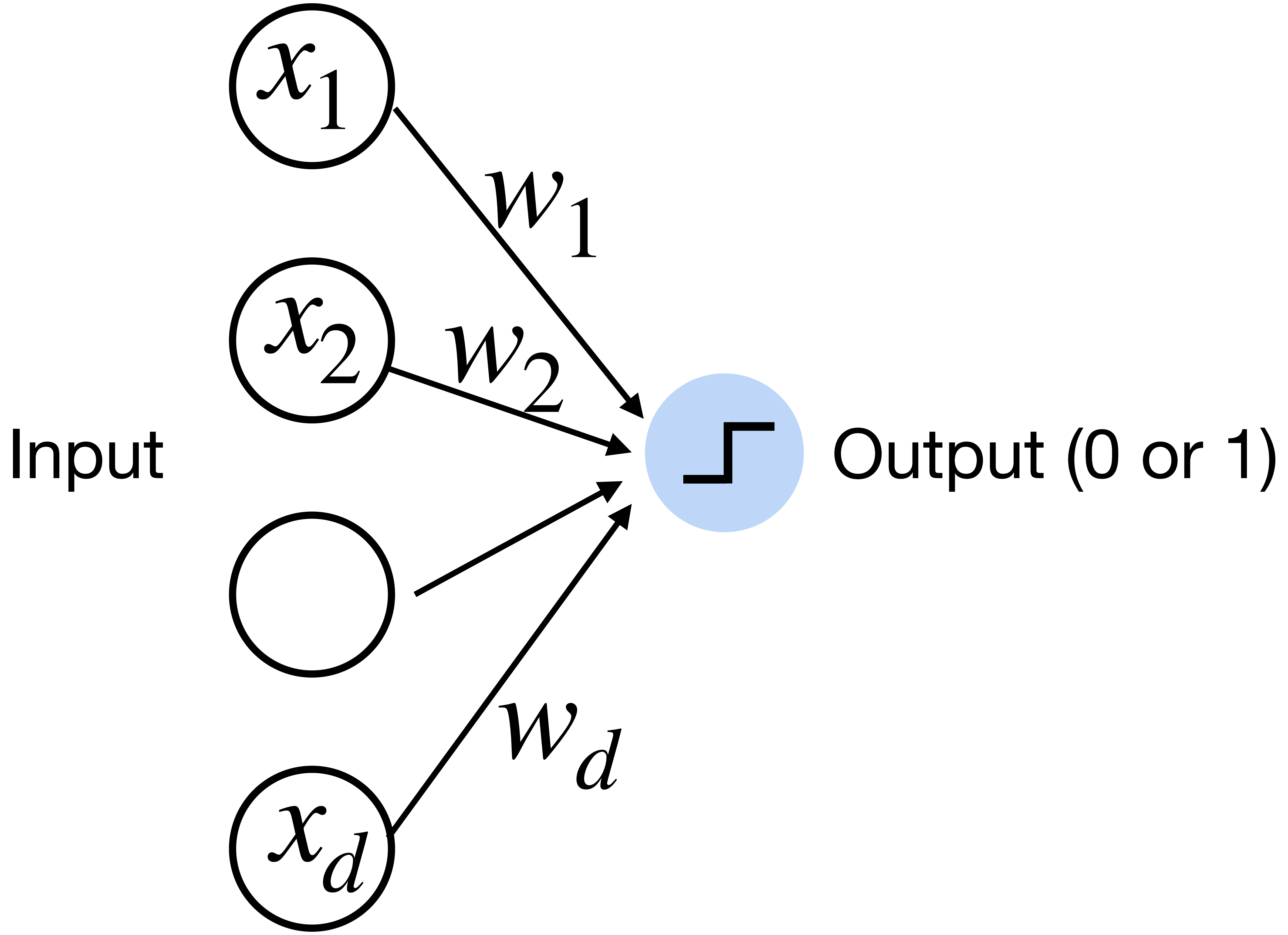


# Perceptron

- Given input $\mathbf{x}$, weight $\mathbf{w}$ and bias $b$, perceptron outputs:

$$o = \sigma\left(\mathbf{w}^\top \mathbf{x} + b\right) \qquad \sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

**Cats vs. dogs?**



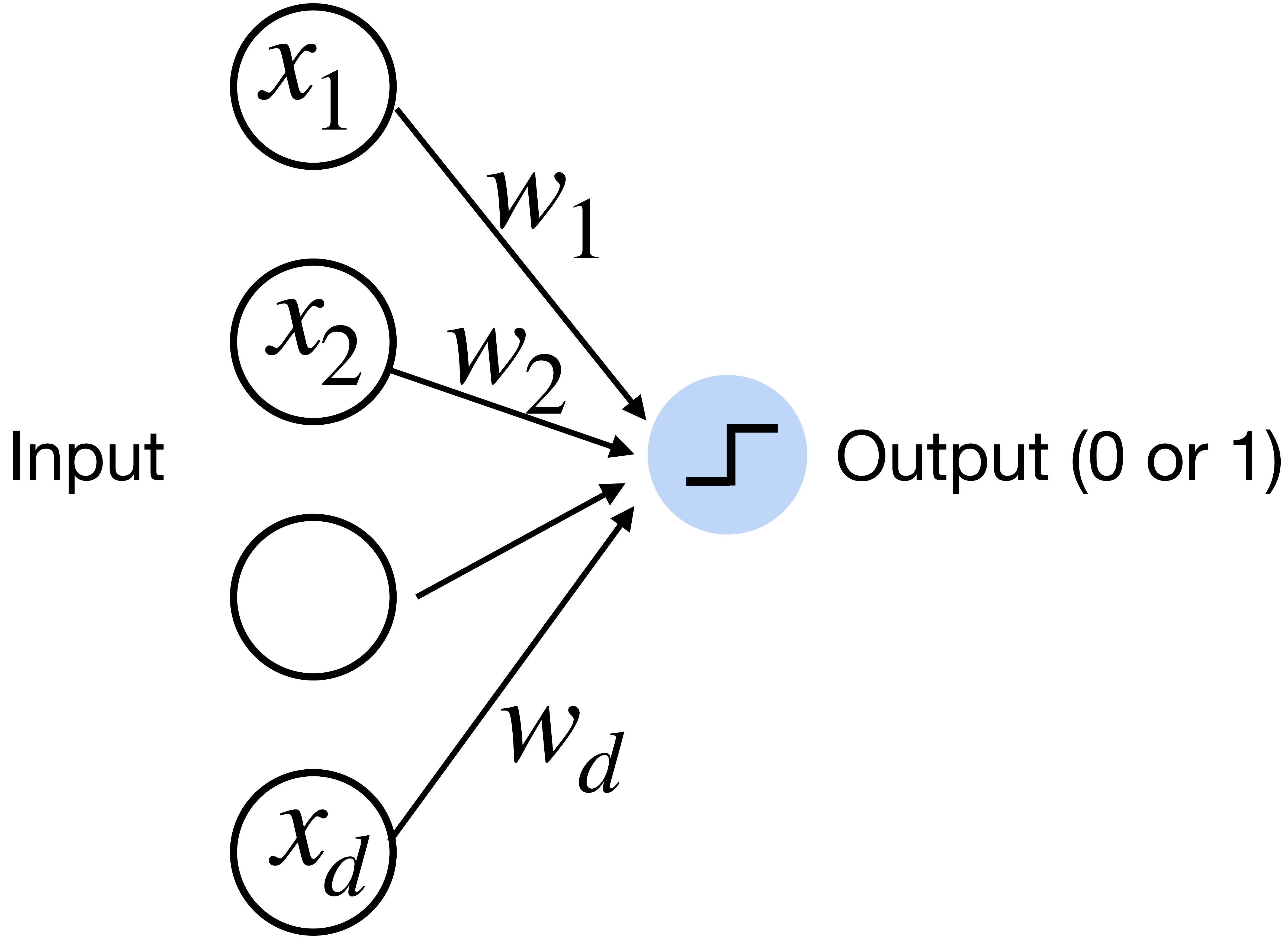
# Perceptron

- Given input $\mathbf{x}$, weight $\mathbf{w}$ and bias $b$, perceptron outputs:

$$o = \sigma\left(\mathbf{w}^\top \mathbf{x} + b\right) \qquad \sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

Activation function

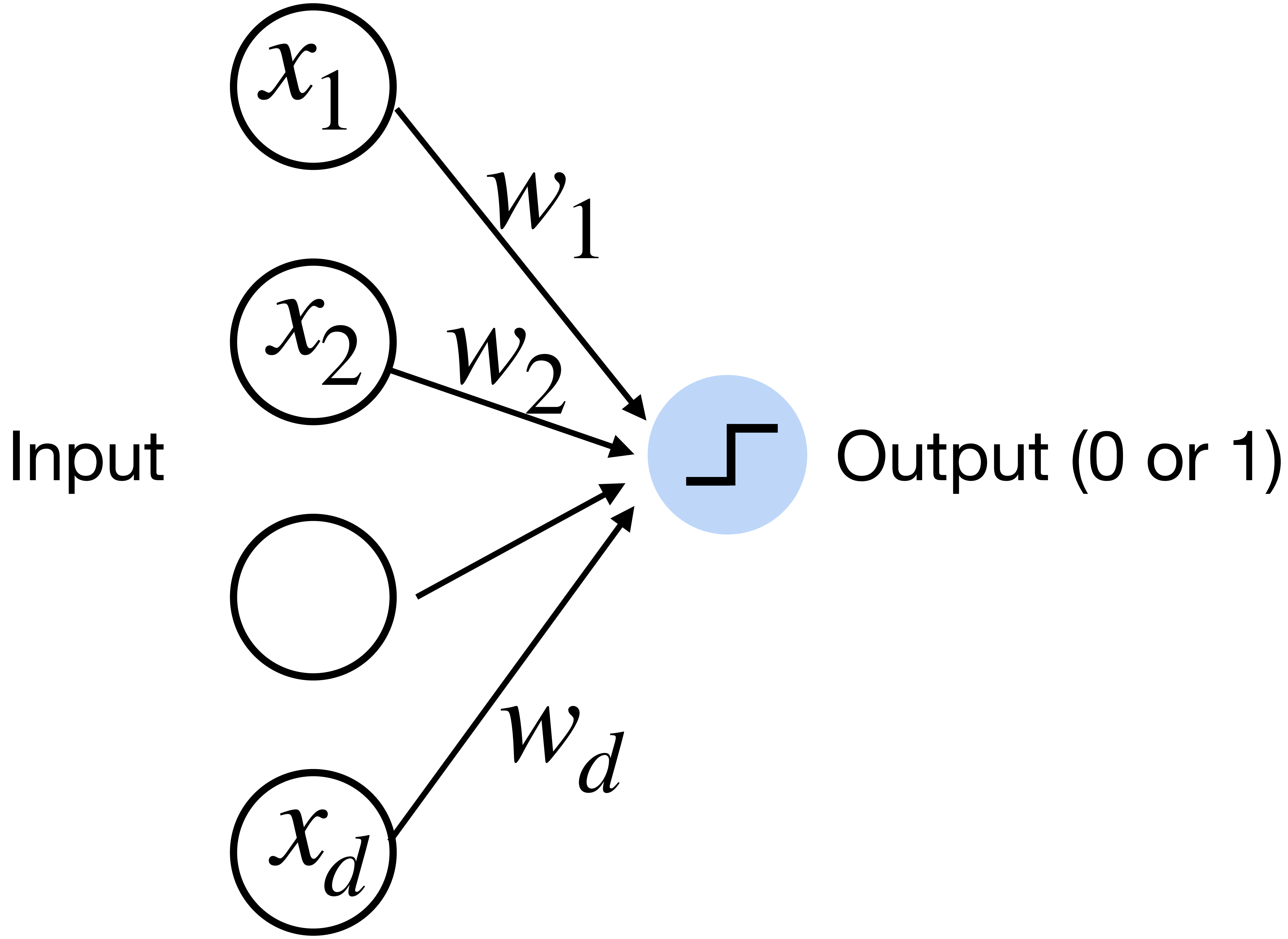
**Cats vs. dogs?**



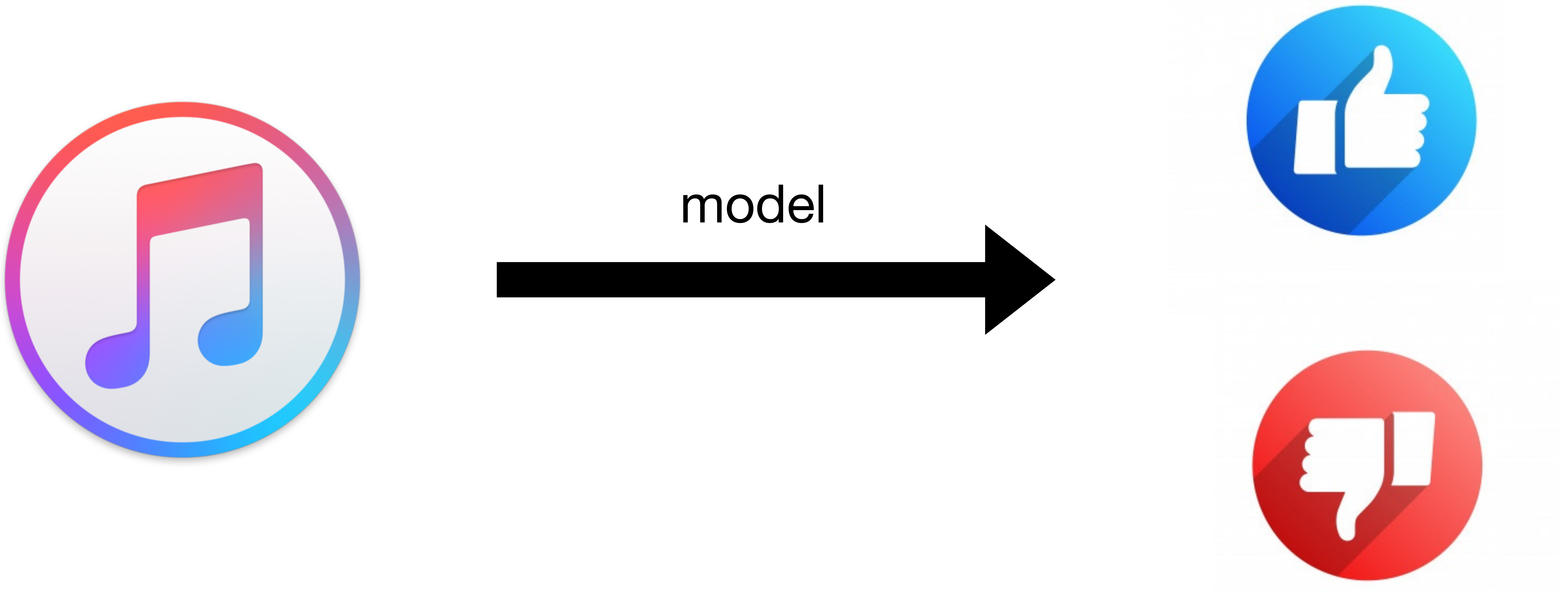
# Perceptron

- Goal: learn parameters $\mathbf{w} = \{w_1, w_2, \ldots, w_d\}$ and b to minimize the classification error

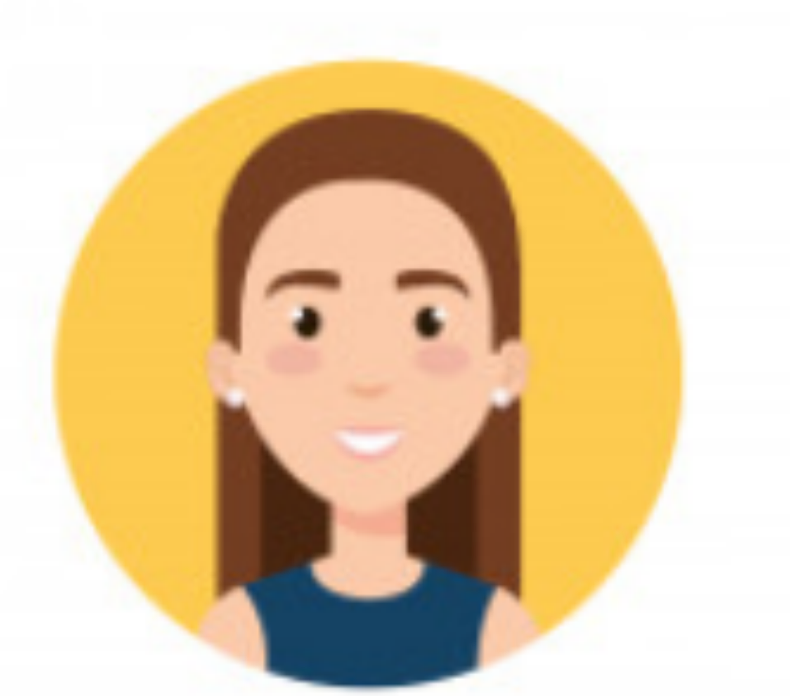
**Cats vs. dogs?**



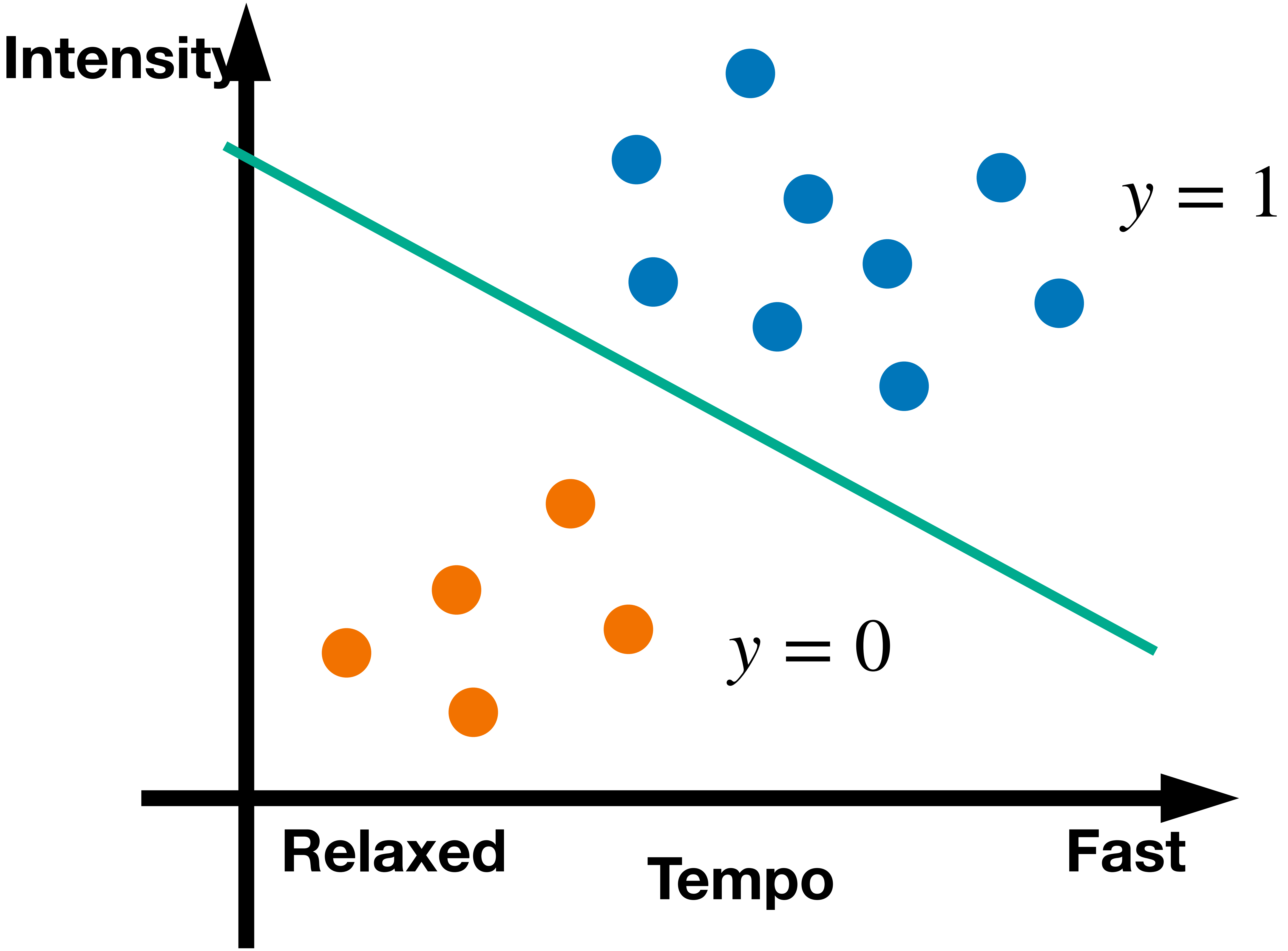
# Example: Predict whether a user likes a song or not



# Example: Predict whether a user likes a song or not Using Perceptron



User Sharon



# Learning logic functions using perceptron

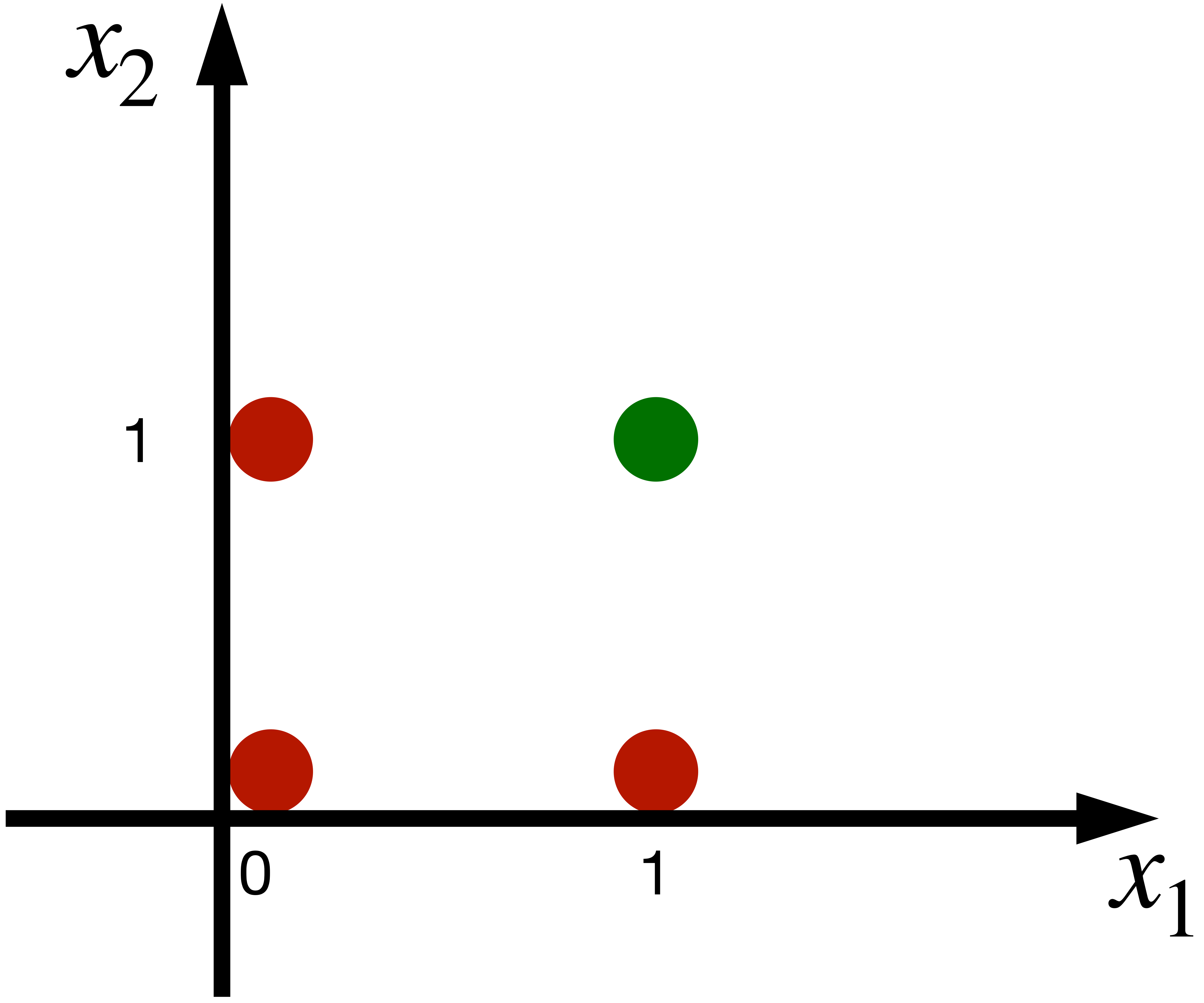
The perceptron can learn an AND function

$x_1 = 1, x_2 = 1, y = 1$

$x_1 = 1, x_2 = 0, y = 0$

$x_1 = 0, x_2 = 1, y = 0$

$x_1 = 0, x_2 = 0, y = 0$



# Learning logic functions using perceptron

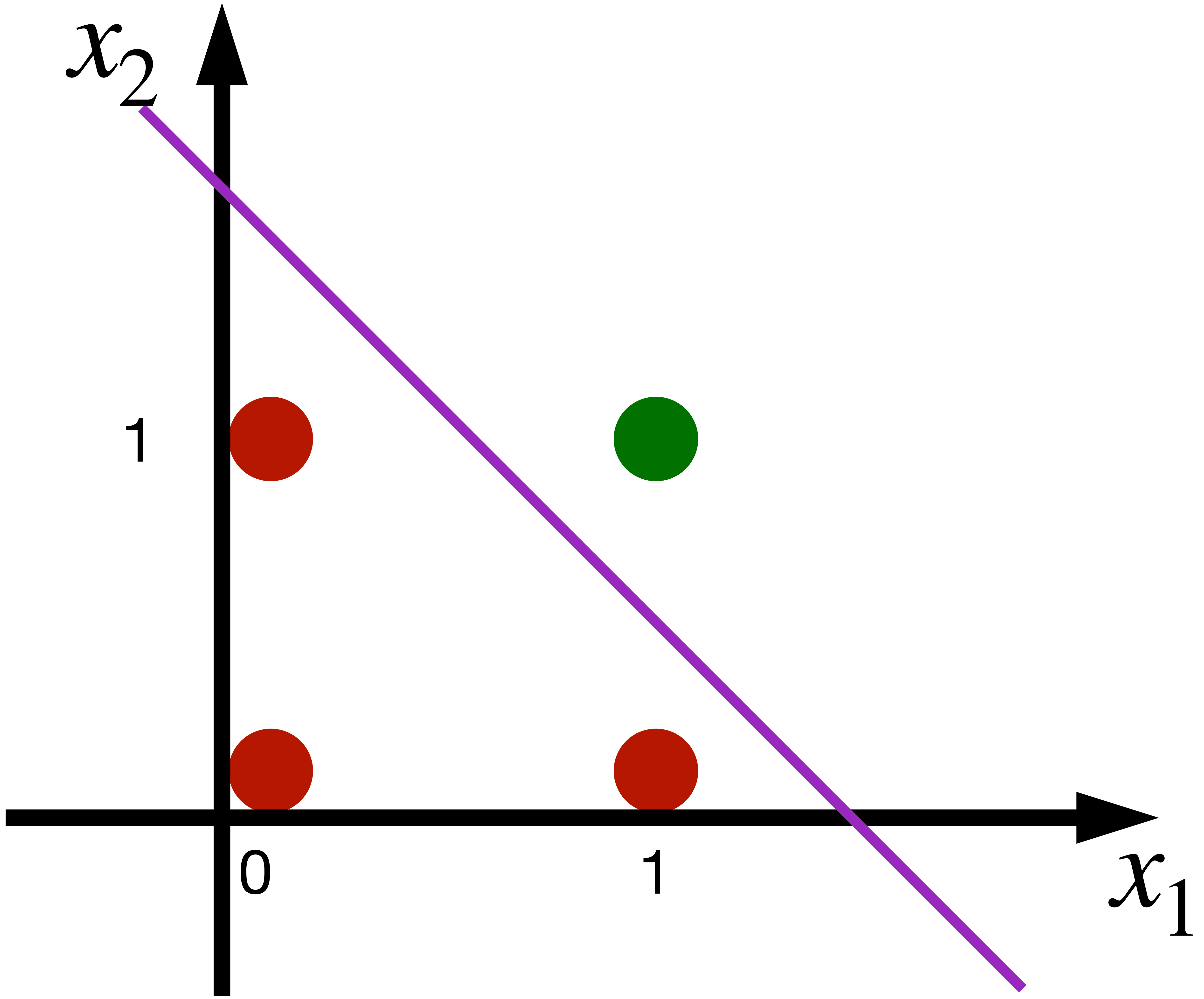
The perceptron can learn an AND function

$x_1 = 1, x_2 = 1, y = 1$

$x_1 = 1, x_2 = 0, y = 0$

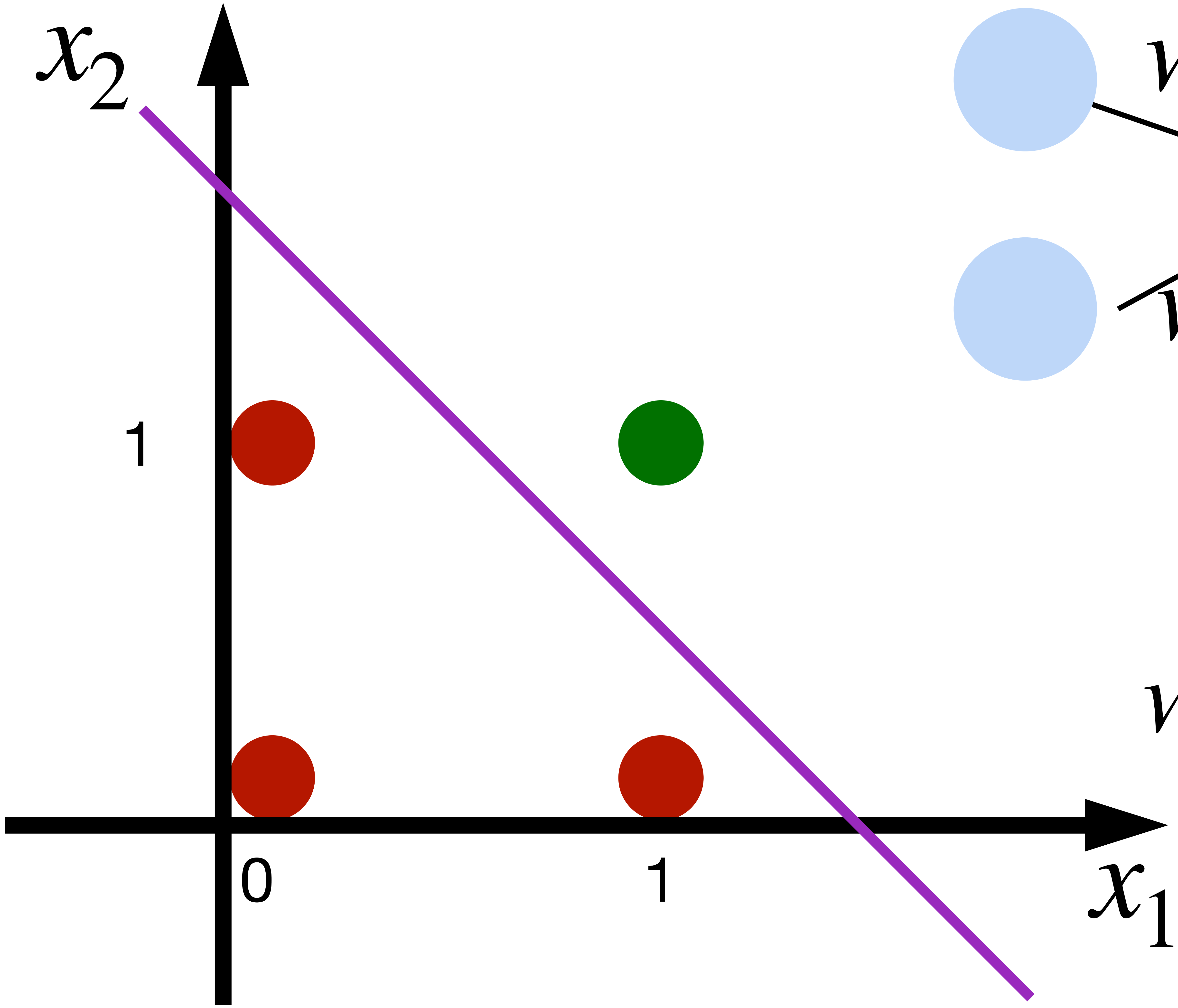
$x_1 = 0, x_2 = 1, y = 0$

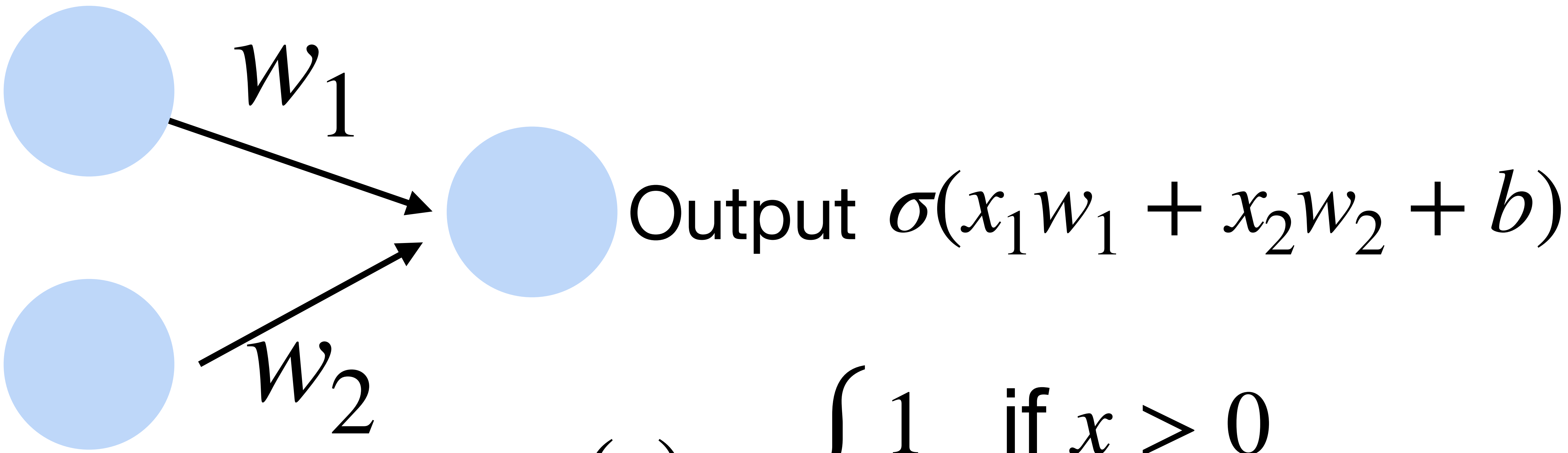
$x_1 = 0, x_2 = 0, y = 0$



# Learning logic functions using perceptron

The perceptron can learn an AND function



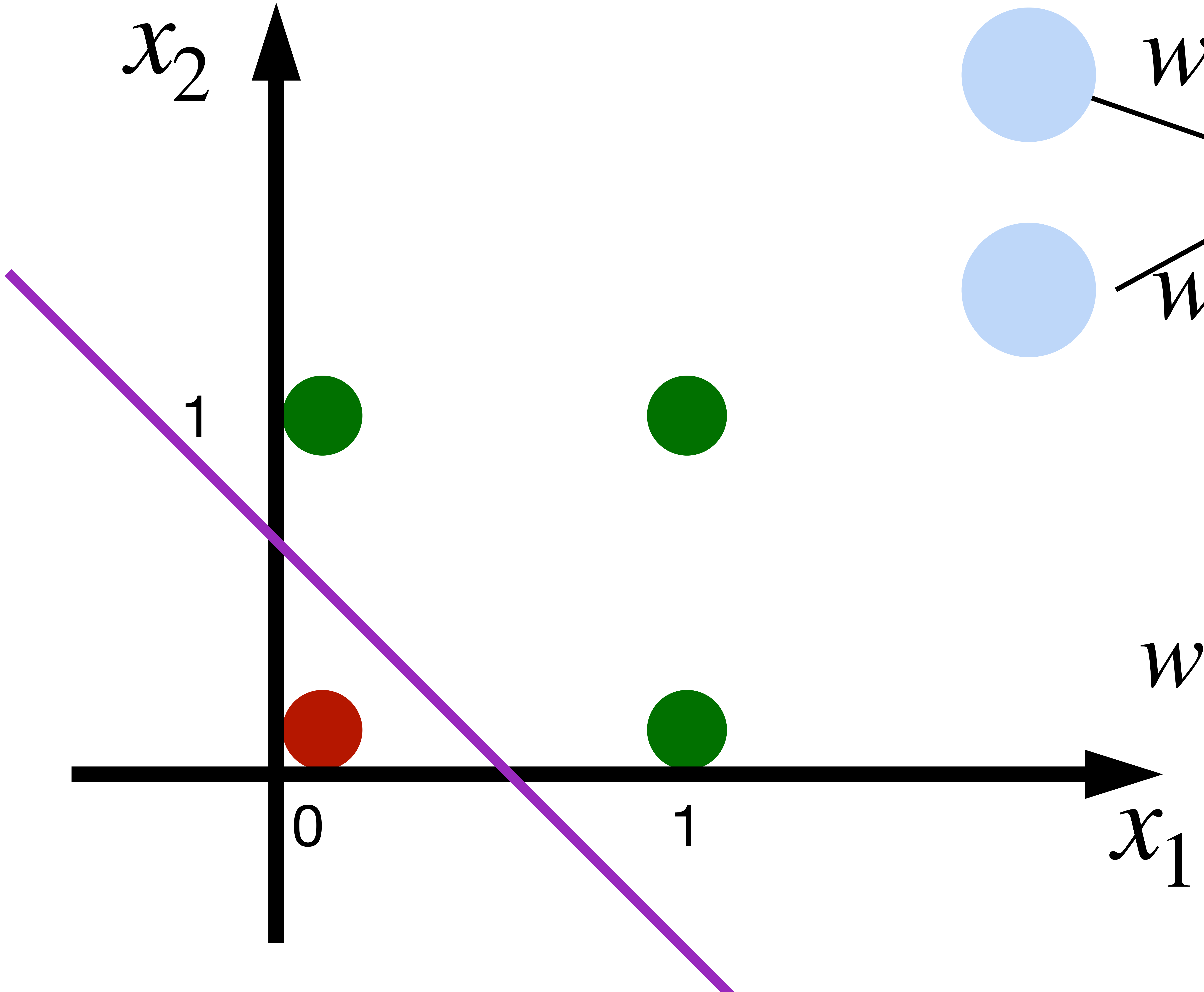



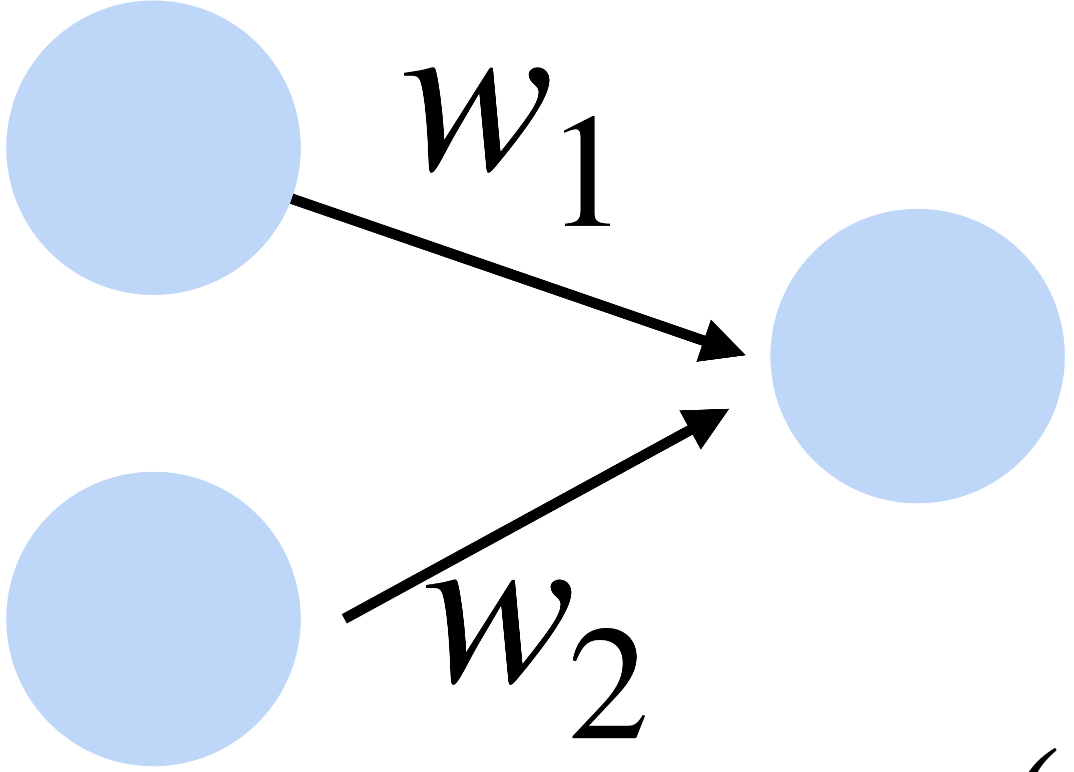

$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$w_1 = 1, w_2 = 1, b = -1.5$$

# Learning OR function using perceptron

The perceptron can learn an OR function




Output $\sigma(x_1 w_1 + x_2 w_2 + b)$

$$\sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$w_1 = 1, w_2 = 1, b = -0.5$$

# XOR Problem (Minsky & Papert, 1969)

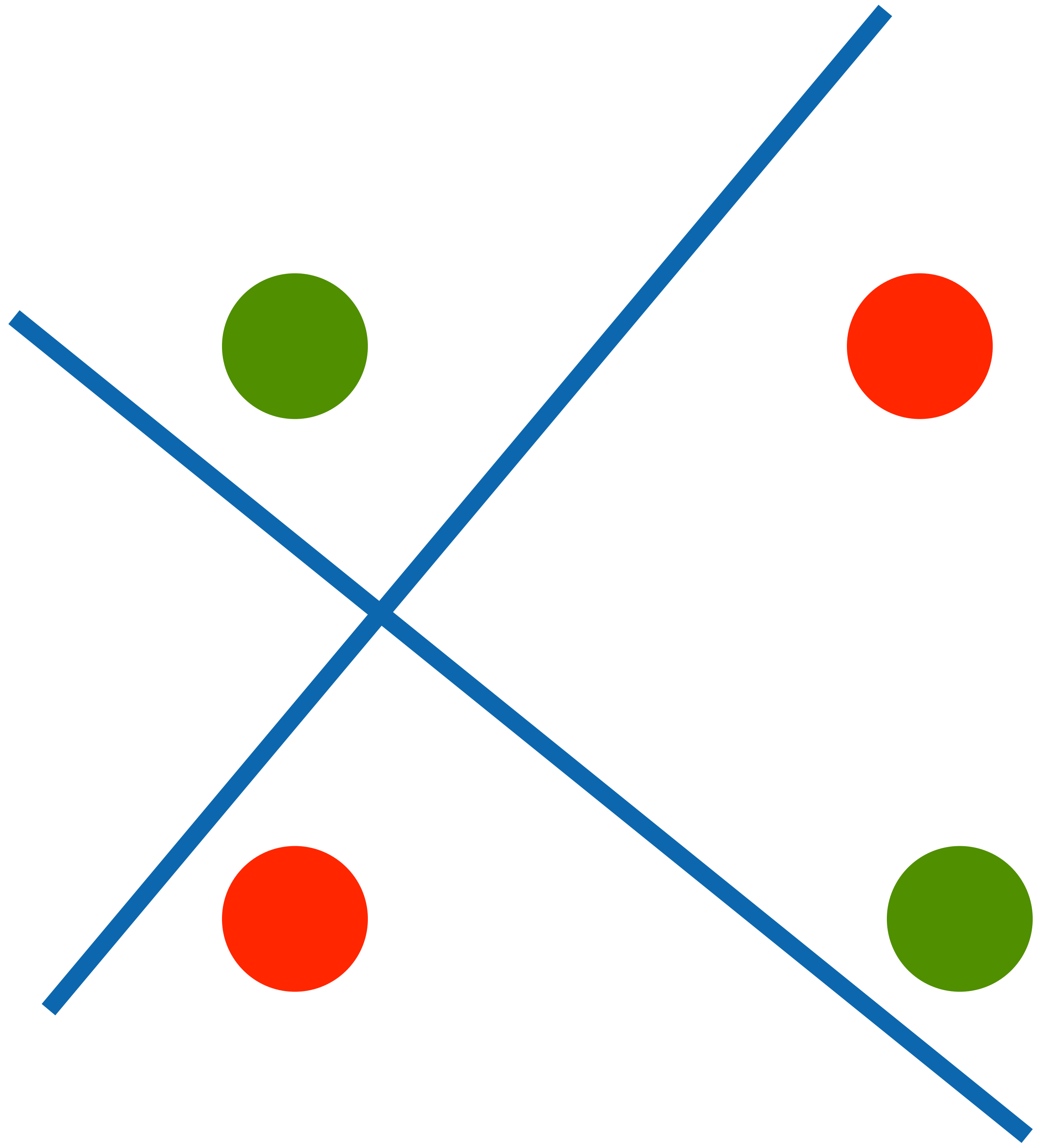
The perceptron cannot learn an XOR function
(neurons can only generate linear separators)

$x_1 = 1, x_2 = 1, y = 0$

$x_1 = 1, x_2 = 0, y = 1$

$x_1 = 0, x_2 = 1, y = 1$

$x_1 = 0, x_2 = 0, y = 0$



# XOR Problem (Minsky & Papert, 1969)

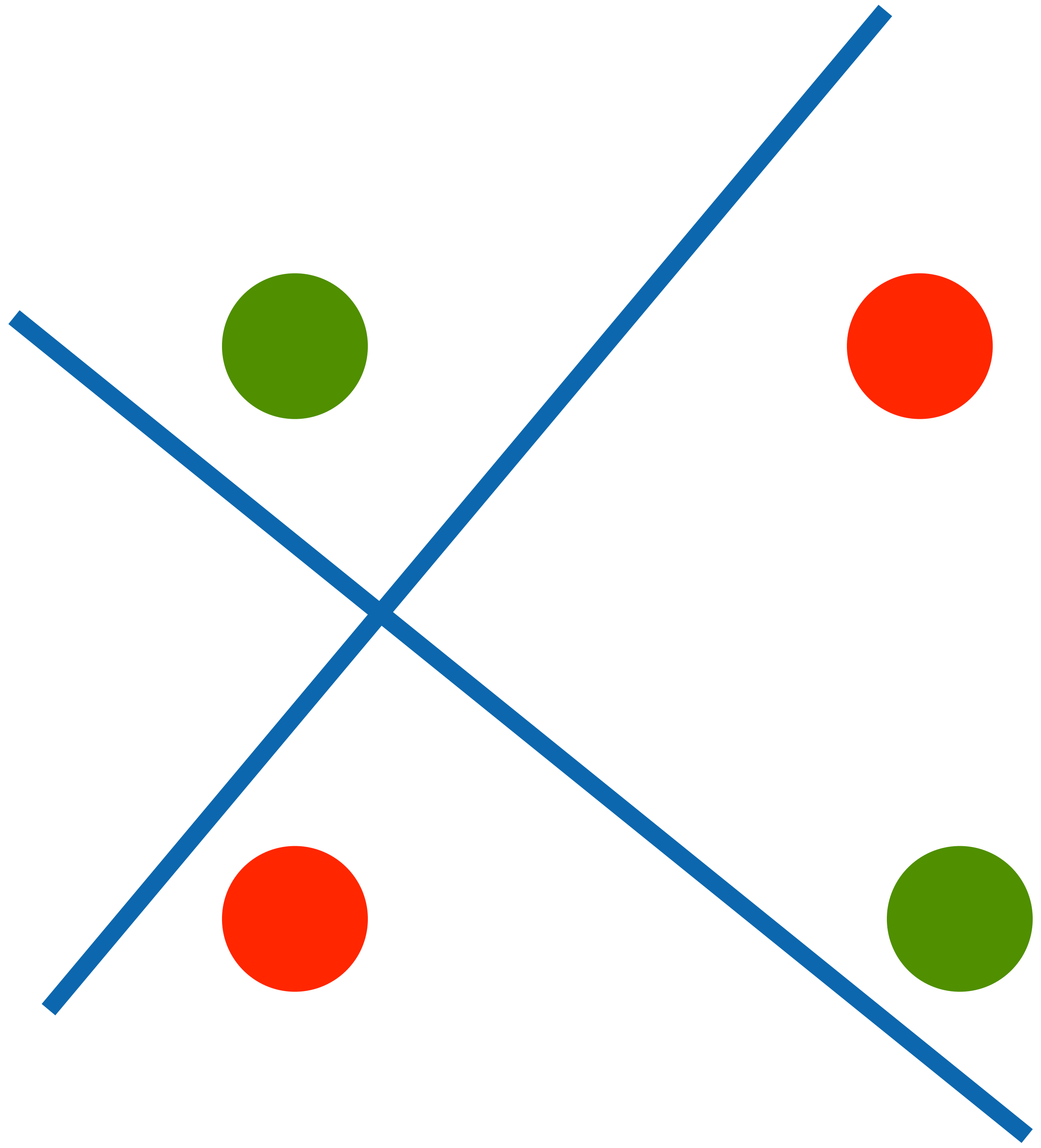
The perceptron cannot learn an XOR function
(neurons can only generate linear separators)

$x_1 = 1, x_2 = 1, y = 0$

$x_1 = 1, x_2 = 0, y = 1$

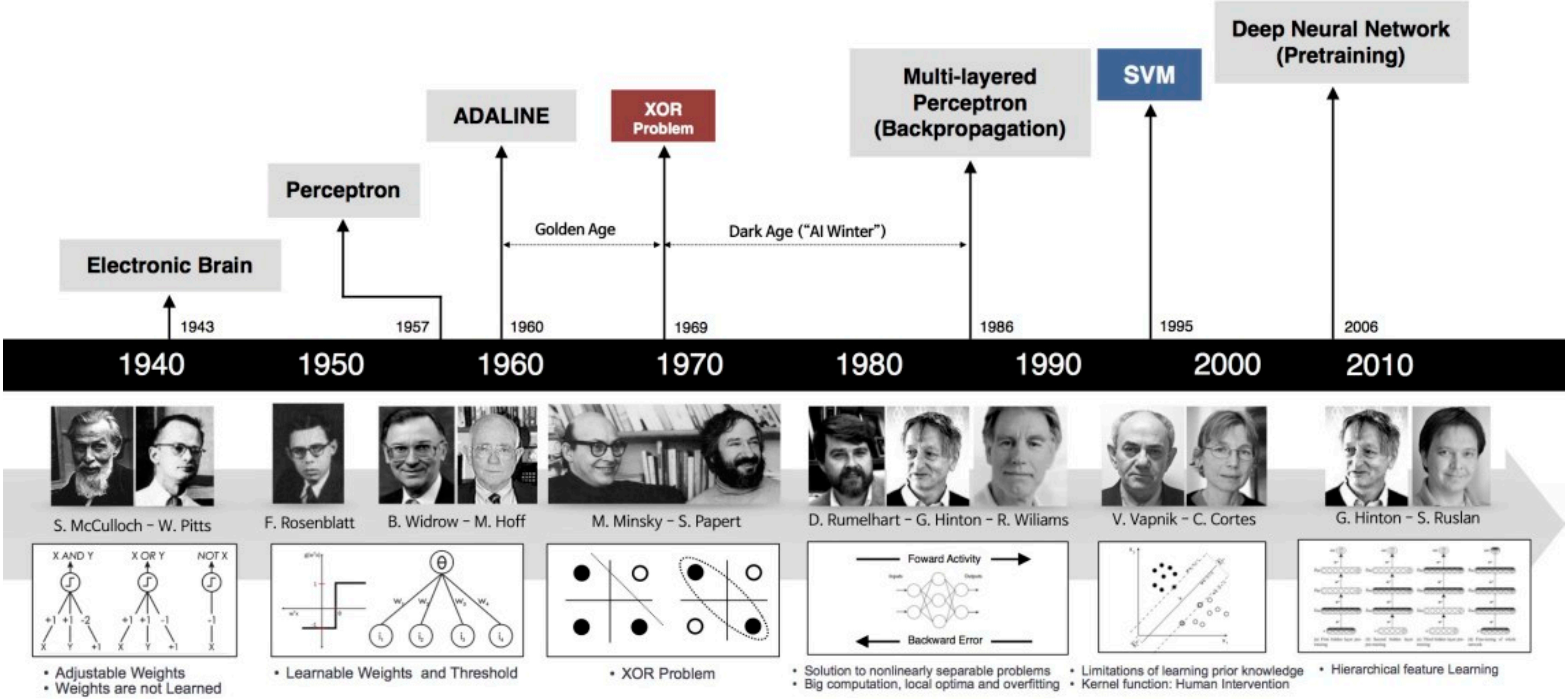
$x_1 = 0, x_2 = 1, y = 1$

$x_1 = 0, x_2 = 0, y = 0$



**This contributed to the first AI winter**

# Brief history of neural networks



# Quiz break

Which one of the following is NOT true about perceptron?

A. Perceptron only works if the data is linearly separable.

B. Perceptron can learn AND function

C. Perceptron can learn XOR function

D. Perceptron is a supervised learning algorithm

# Quiz break

Which one of the following is NOT true about perceptron?

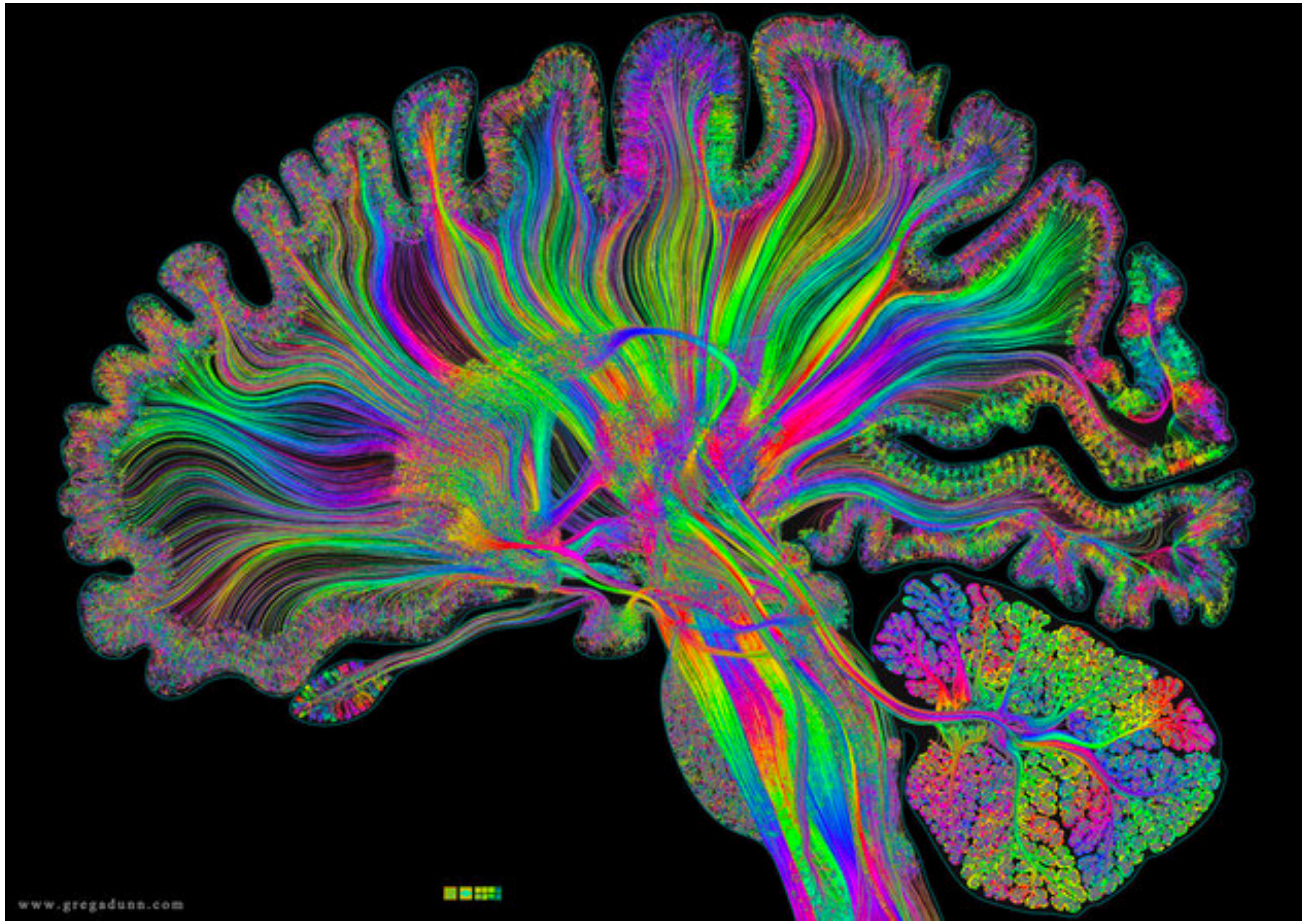
A. Perceptron only works if the data is linearly separable.

B. Perceptron can learn AND function

C. Perceptron can learn XOR function

D. Perceptron is a supervised learning algorithm

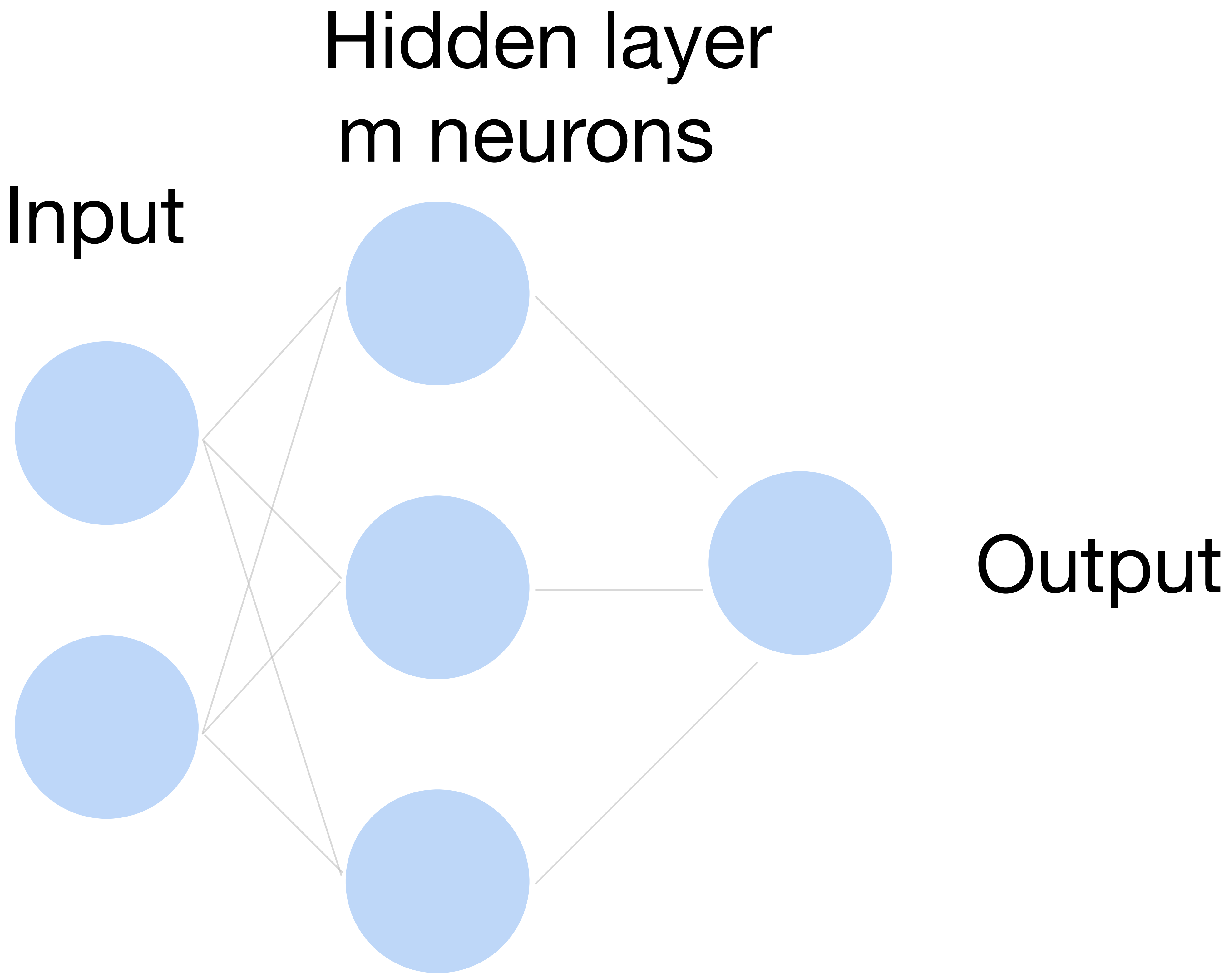
# Multilayer Perceptron



# Single Hidden Layer

## How to classify

**Cats vs. dogs?**

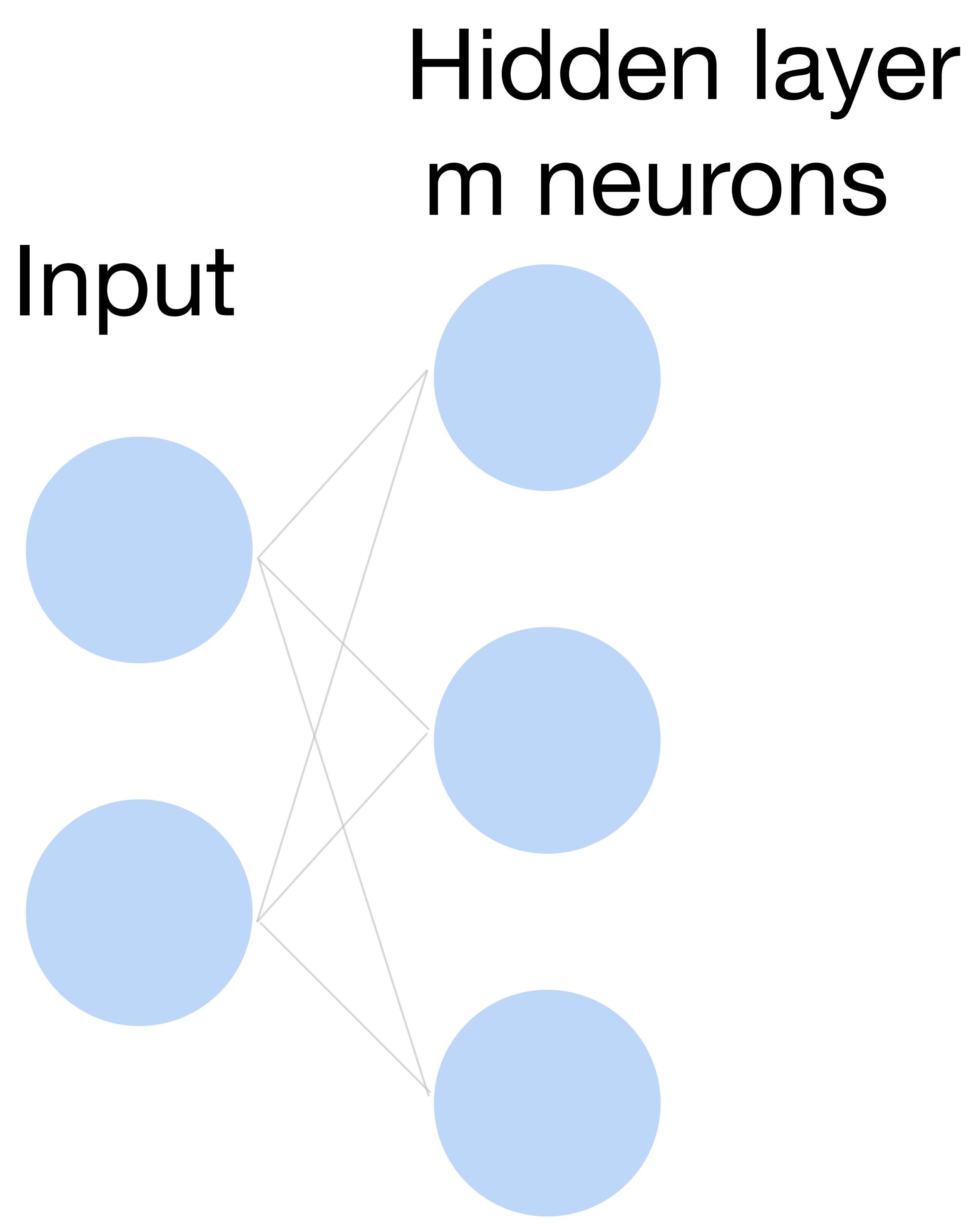


# Single Hidden Layer

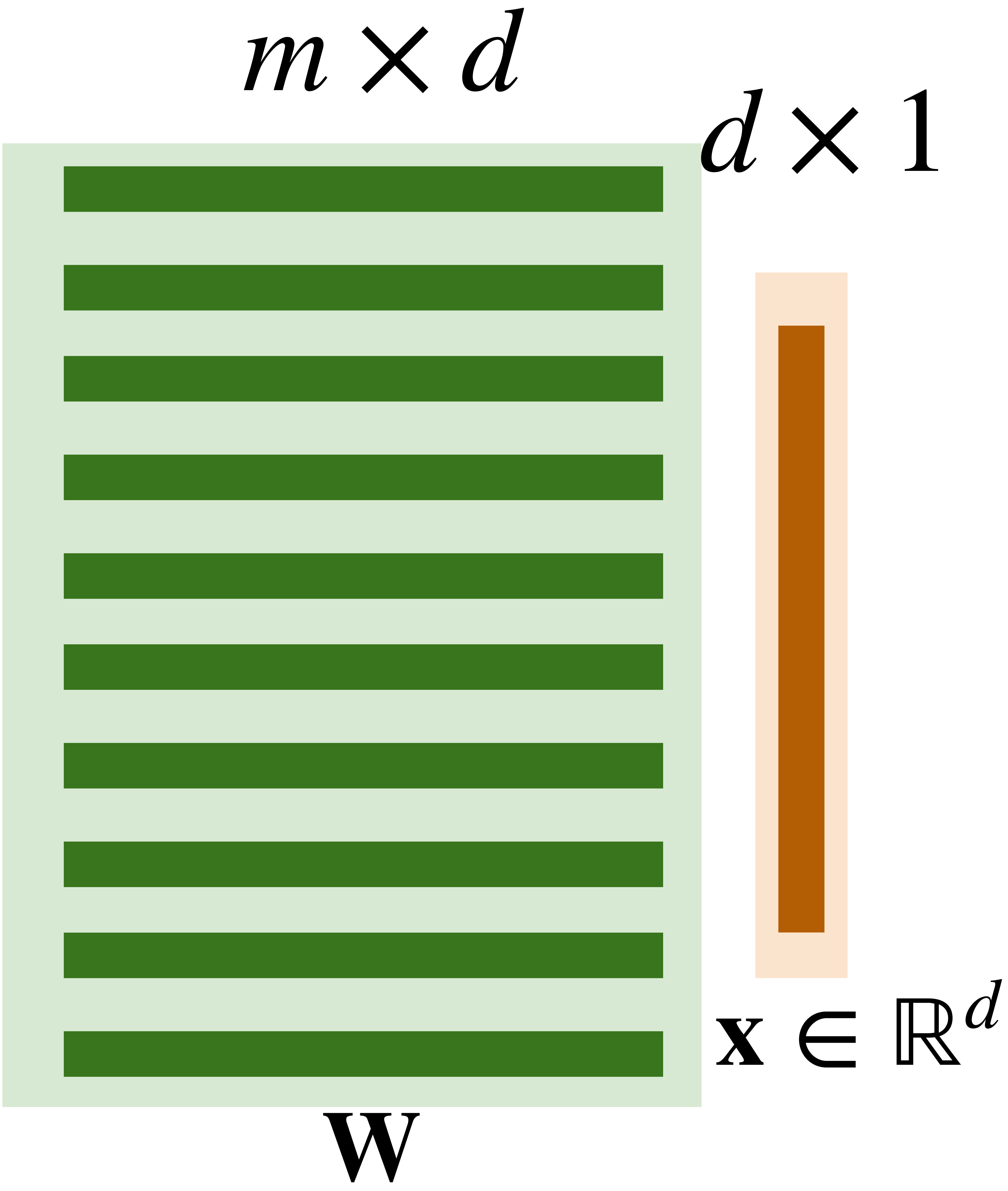
- Input $\mathbf{x} \in \mathbb{R}^d$
- Hidden $\mathbf{W} \in \mathbb{R}^{m \times d}, \mathbf{b} \in \mathbb{R}^m$
- Intermediate output

$$\mathbf{h} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$$

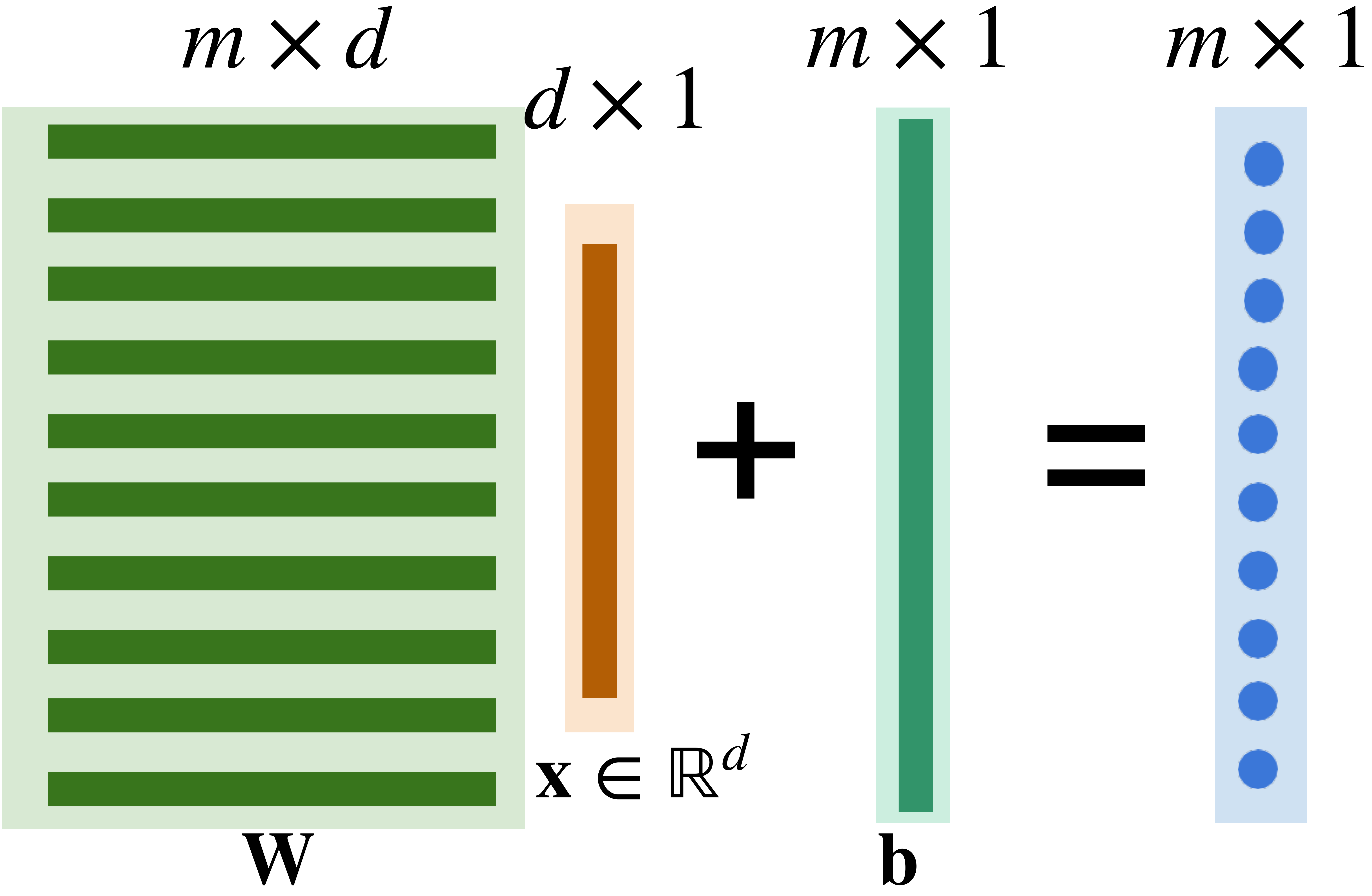
$\sigma$ is an element-wise activation function



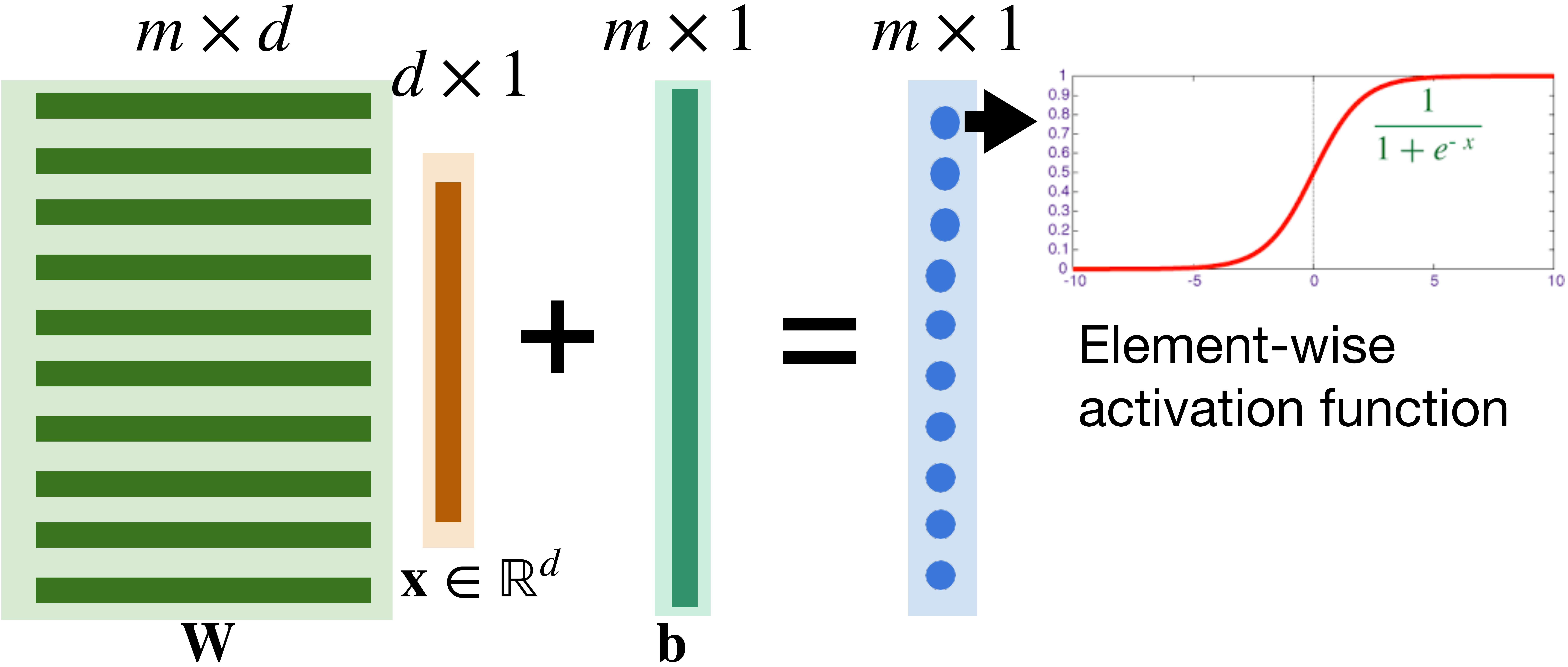
# Neural networks with one hidden layer



# Neural networks with one hidden layer

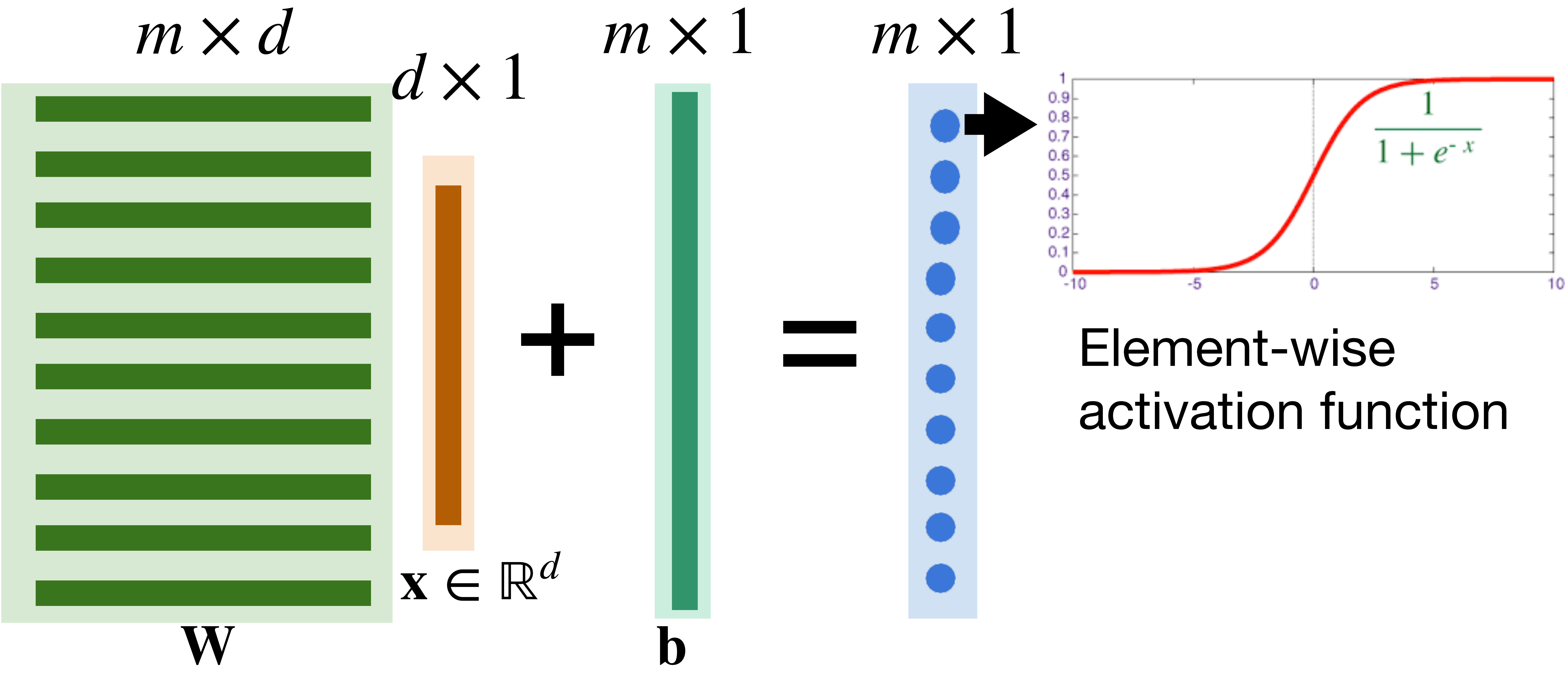


# Neural networks with one hidden layer



# Neural networks with one hidden layer

**Key elements:** linear operations + Nonlinear activations

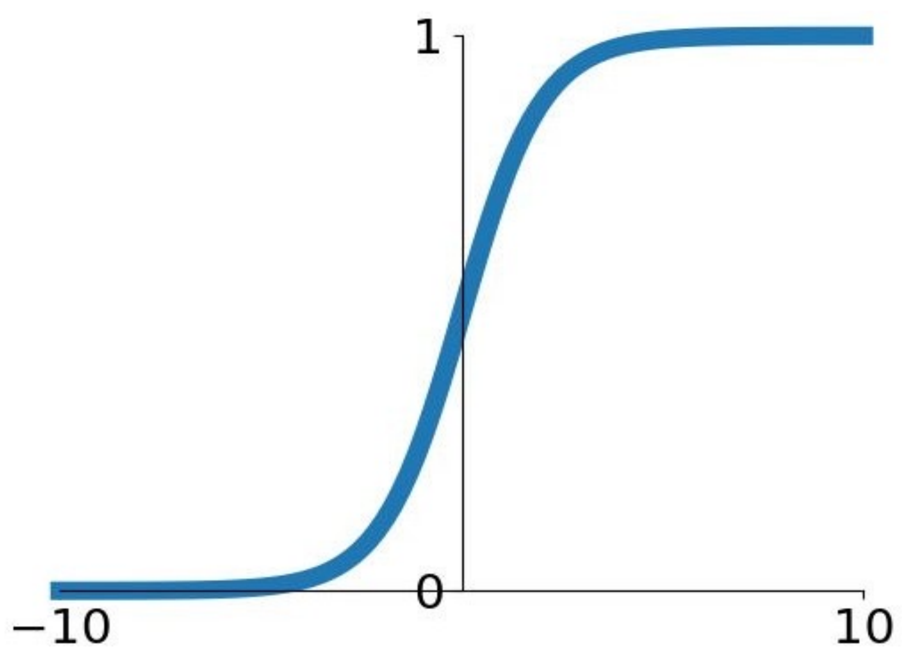


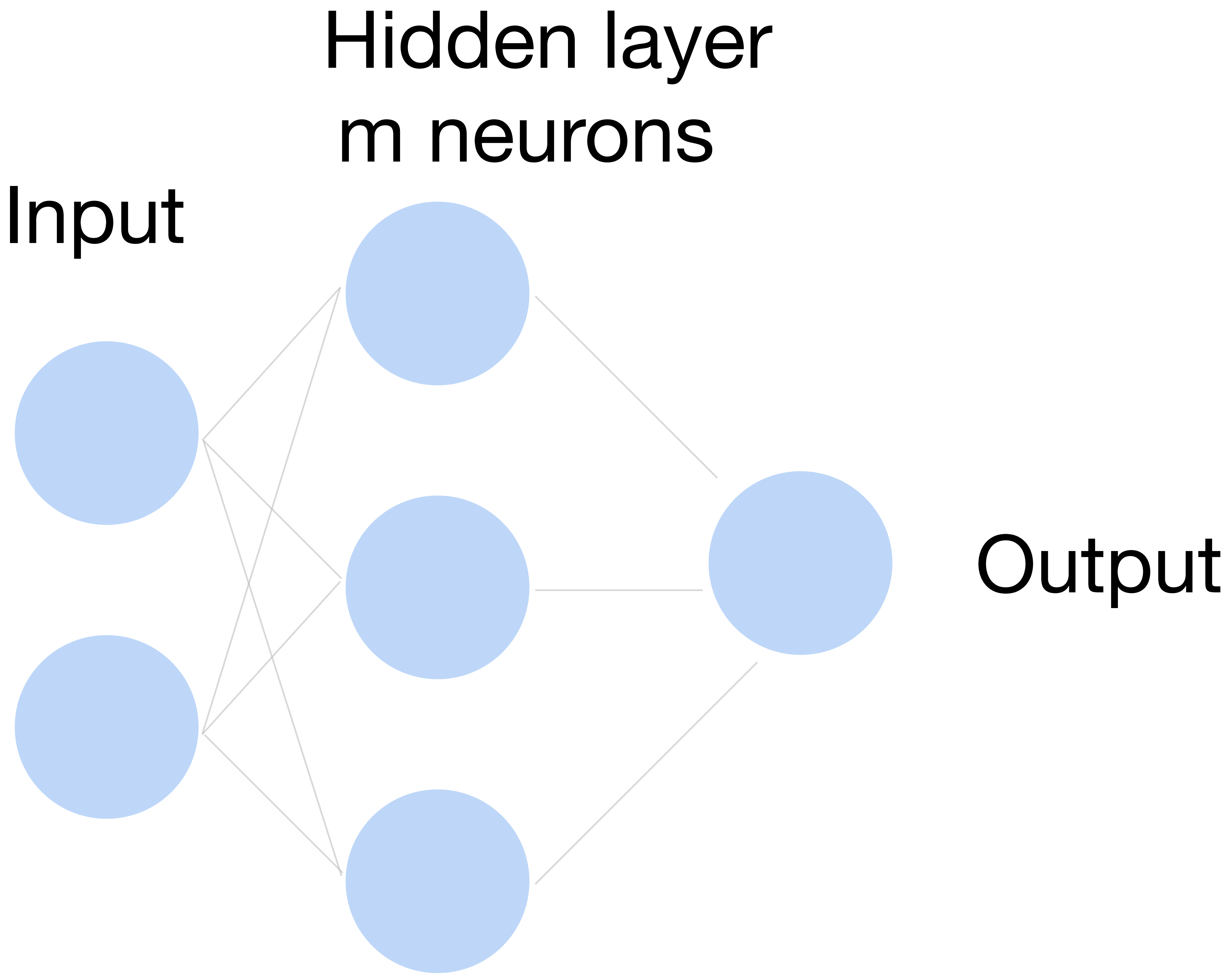
# Single Hidden Layer

- Output $f = \mathbf{w}_2^\top \mathbf{h} + b_2$
- Normalize the output into probability using sigmoid

$$p(y = 1 \mid \mathbf{x}) = \frac{1}{1 + e^{-f}}$$

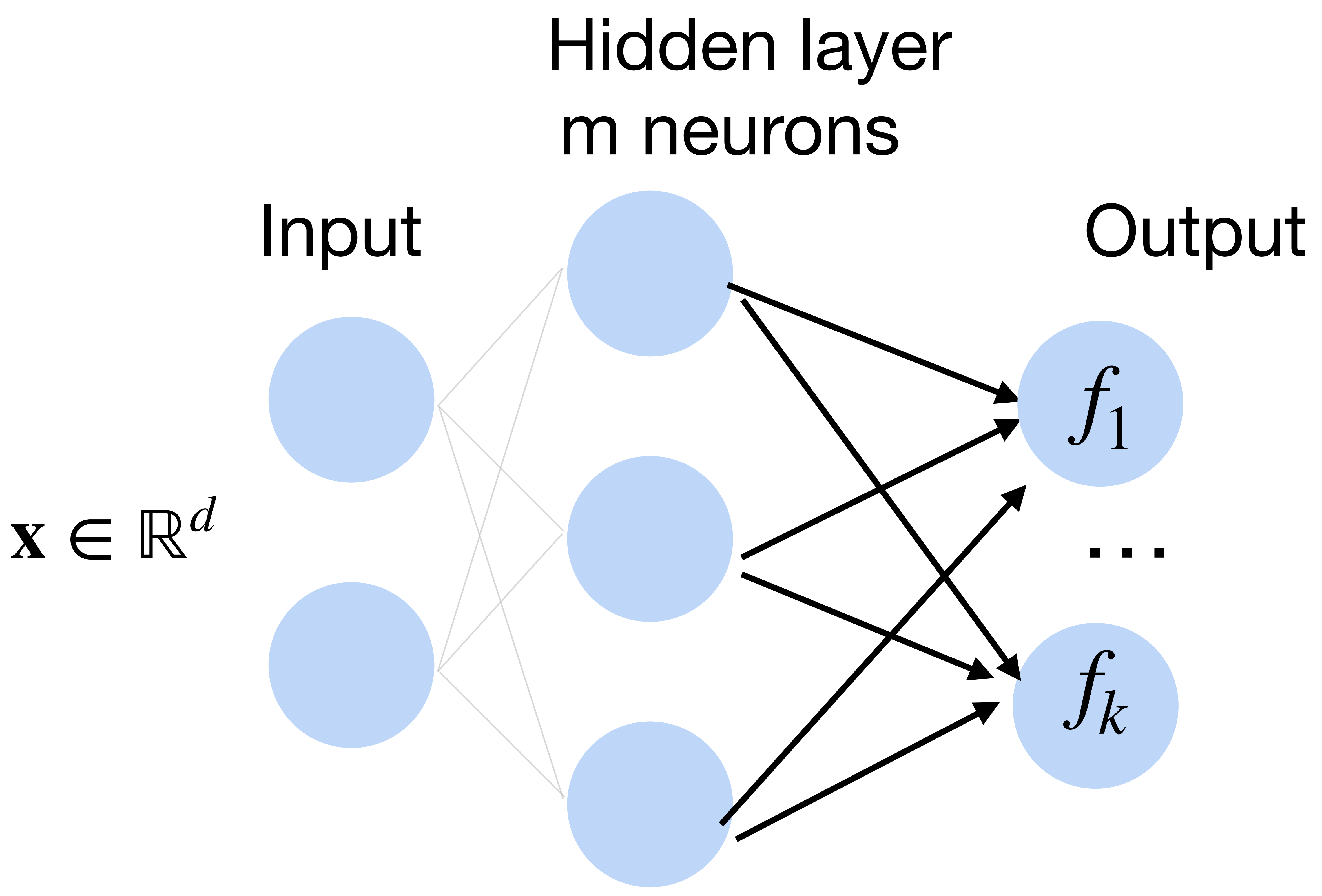
**Sigmoid**



# Multi-class classification

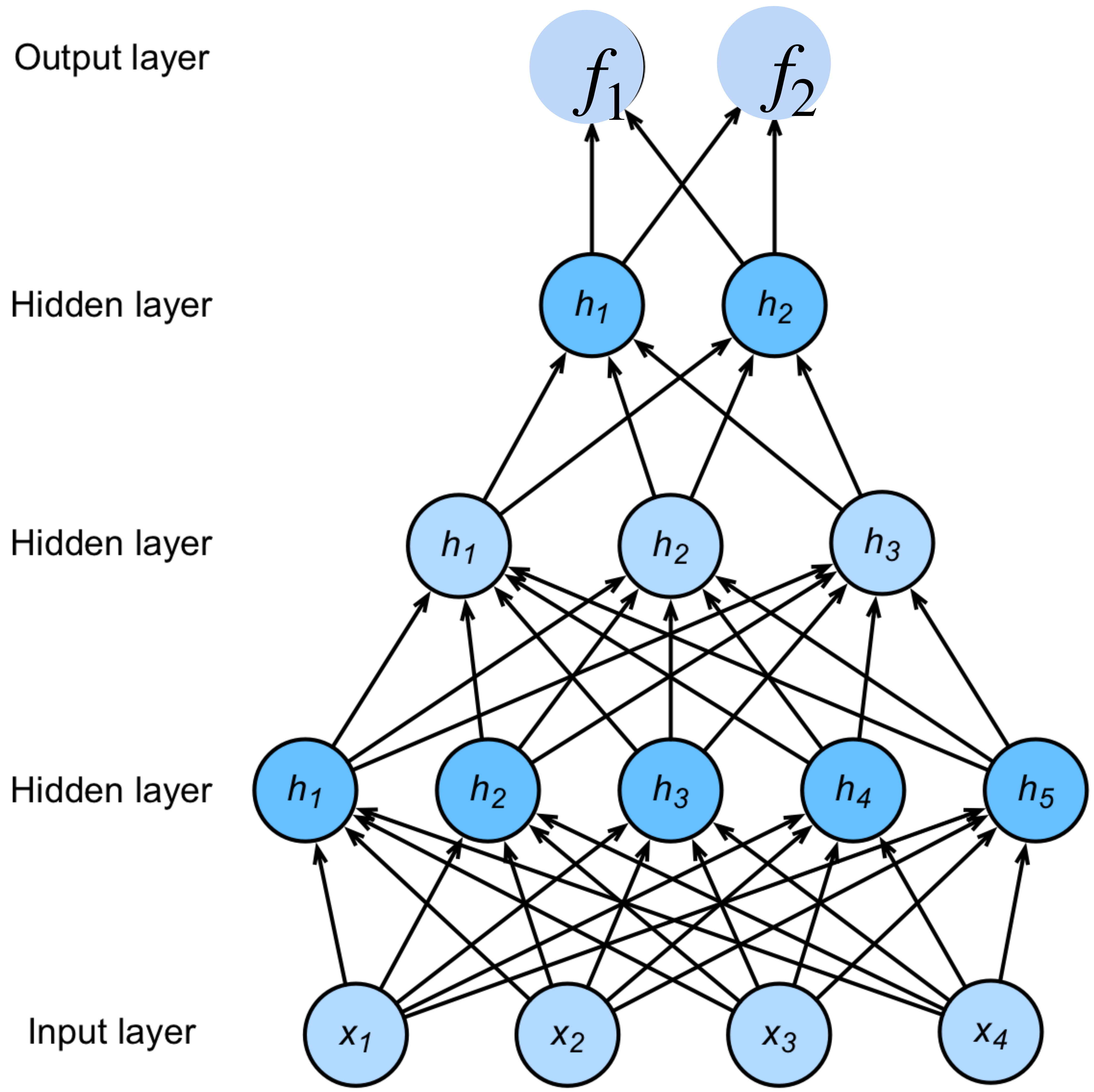
Turns outputs f into k probabilities (sum up to 1 across k classes)




$$p(y \mid \mathbf{x}) = \text{softmax}(\mathbf{f})$$

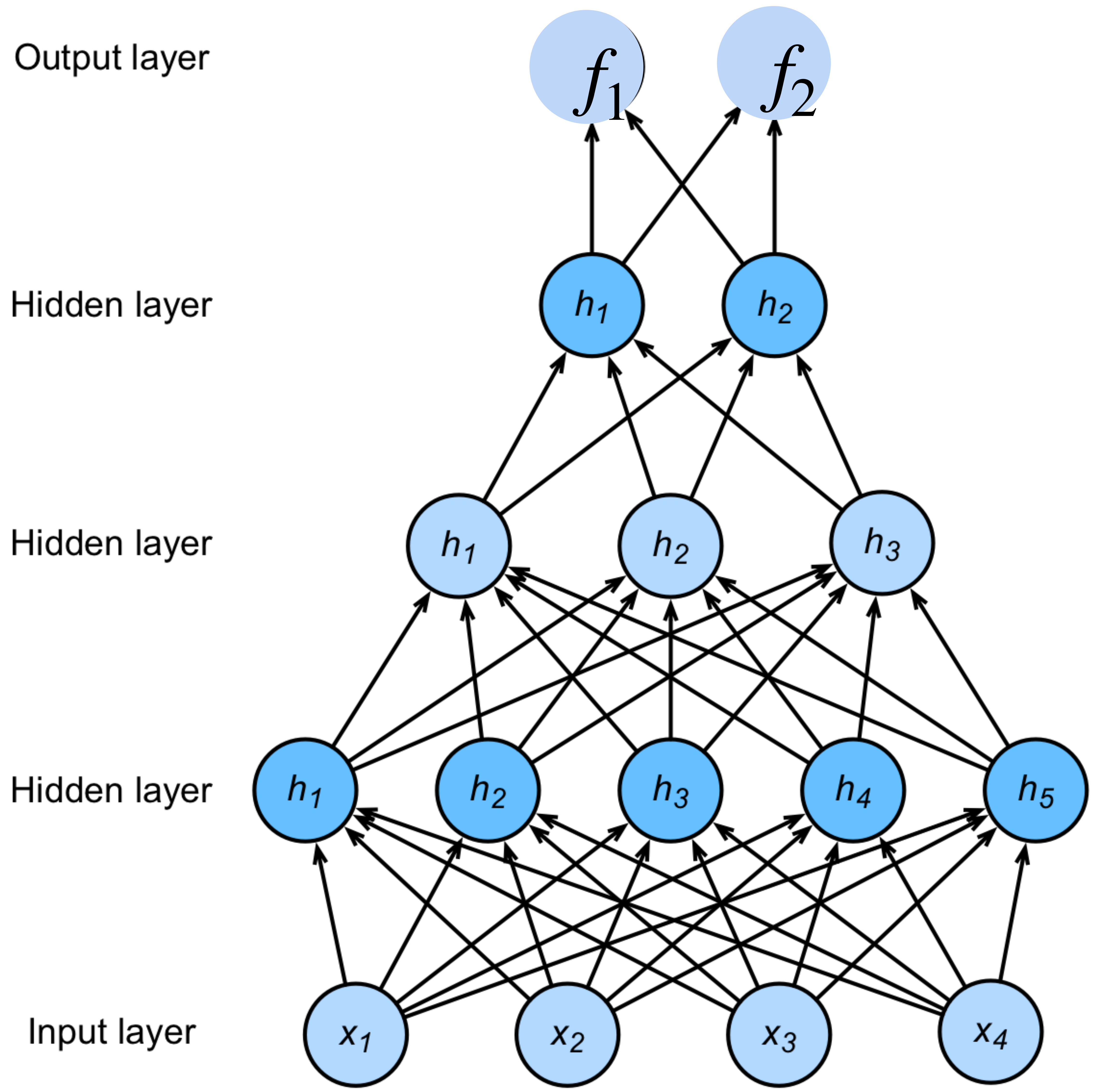
$$= \frac{\exp f_y(x)}{\sum_i^k \exp f_i(x)}$$

# Deep neural networks (DNNs)




$$\mathbf{h}_1 = \sigma(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1)$$
$$\mathbf{h}_2 = \sigma(\mathbf{W}_2\mathbf{h}_1 + \mathbf{b}_2)$$
$$\mathbf{h}_3 = \sigma(\mathbf{W}_3\mathbf{h}_2 + \mathbf{b}_3)$$
$$\mathbf{f} = \mathbf{W}_4\mathbf{h}_3 + \mathbf{b}_4$$
$$\mathbf{y} = \text{softmax}(\mathbf{f})$$

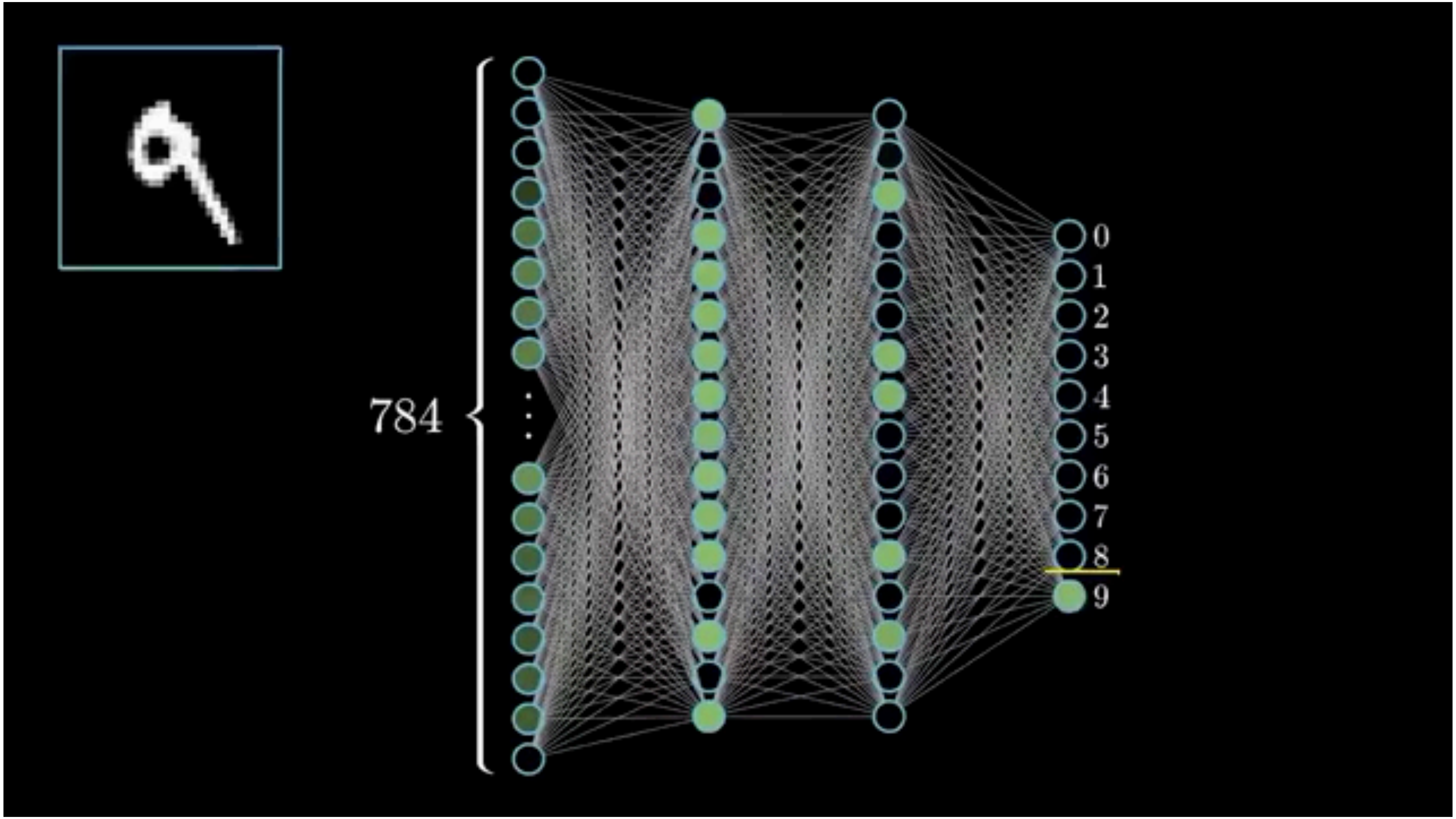
# Deep neural networks (DNNs)



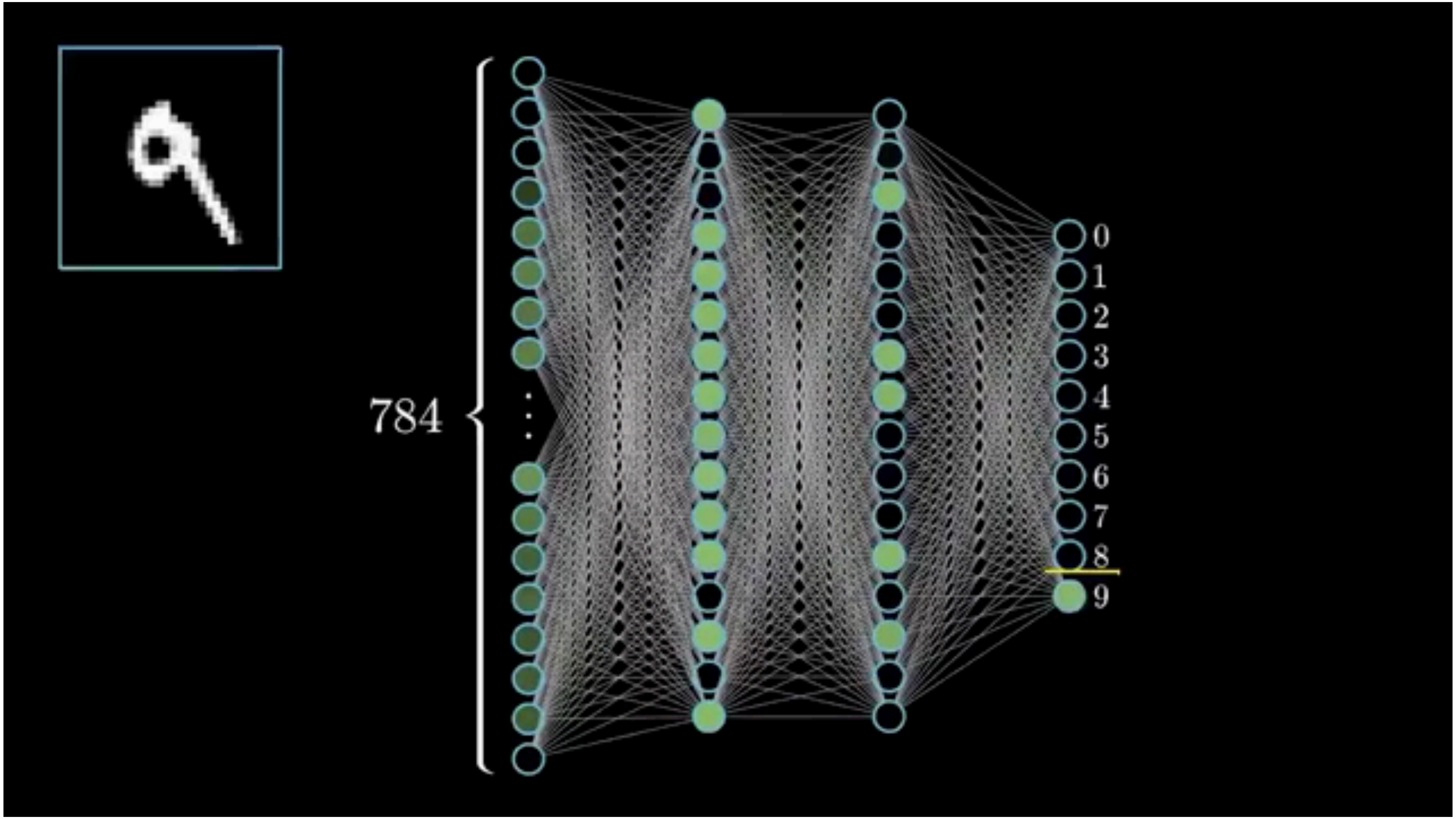

$$\mathbf{h}_1 = \sigma(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1)$$
$$\mathbf{h}_2 = \sigma(\mathbf{W}_2\mathbf{h}_1 + \mathbf{b}_2)$$
$$\mathbf{h}_3 = \sigma(\mathbf{W}_3\mathbf{h}_2 + \mathbf{b}_3)$$
$$\mathbf{f} = \mathbf{W}_4\mathbf{h}_3 + \mathbf{b}_4$$
$$\mathbf{y} = \text{softmax}(\mathbf{f})$$

NNs are composition of nonlinear functions

# Classify MNIST handwritten digits (HW6)



# Classify MNIST handwritten digits (HW6)



# Quiz break

You have a two-layer neural network with 2 units in the hidden layer. All weights have value 1 and all biases have value -1. The hidden layer has relu activations. What value does the network predict for x = [1, -1]?

A. [-3, -3]

B. [-1, -1]

C. [0, 0]

D. [1, 1]

# Quiz break

You have a two-layer neural network with 2 units in the hidden layer. All weights have value 1 and all biases have value -1. The hidden layer has relu activations. What value does the network predict for x = [1, -1]?

A. [-3, -3]

B. [-1, -1]

C. [0, 0]

D. [1, 1]

Wx = [0, 0]

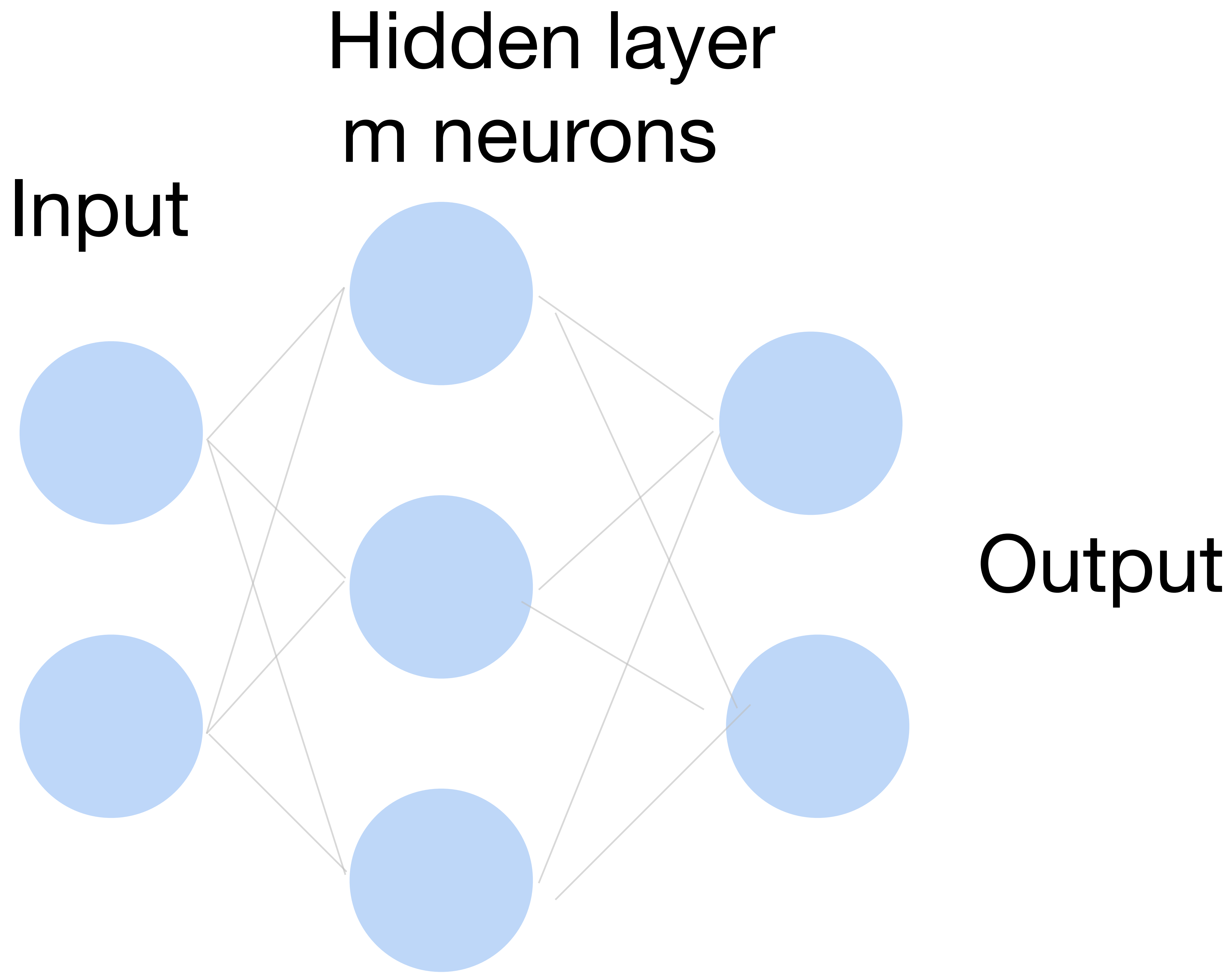
Wx + b = [-1, -1]

h = relu([-1, -1]) = 0

Wh + b = [-1, -1]

# How to train a neural network?

**Loss function:** $\frac{1}{|D|}\sum_i \ell(\mathbf{x}_i, y_i)$

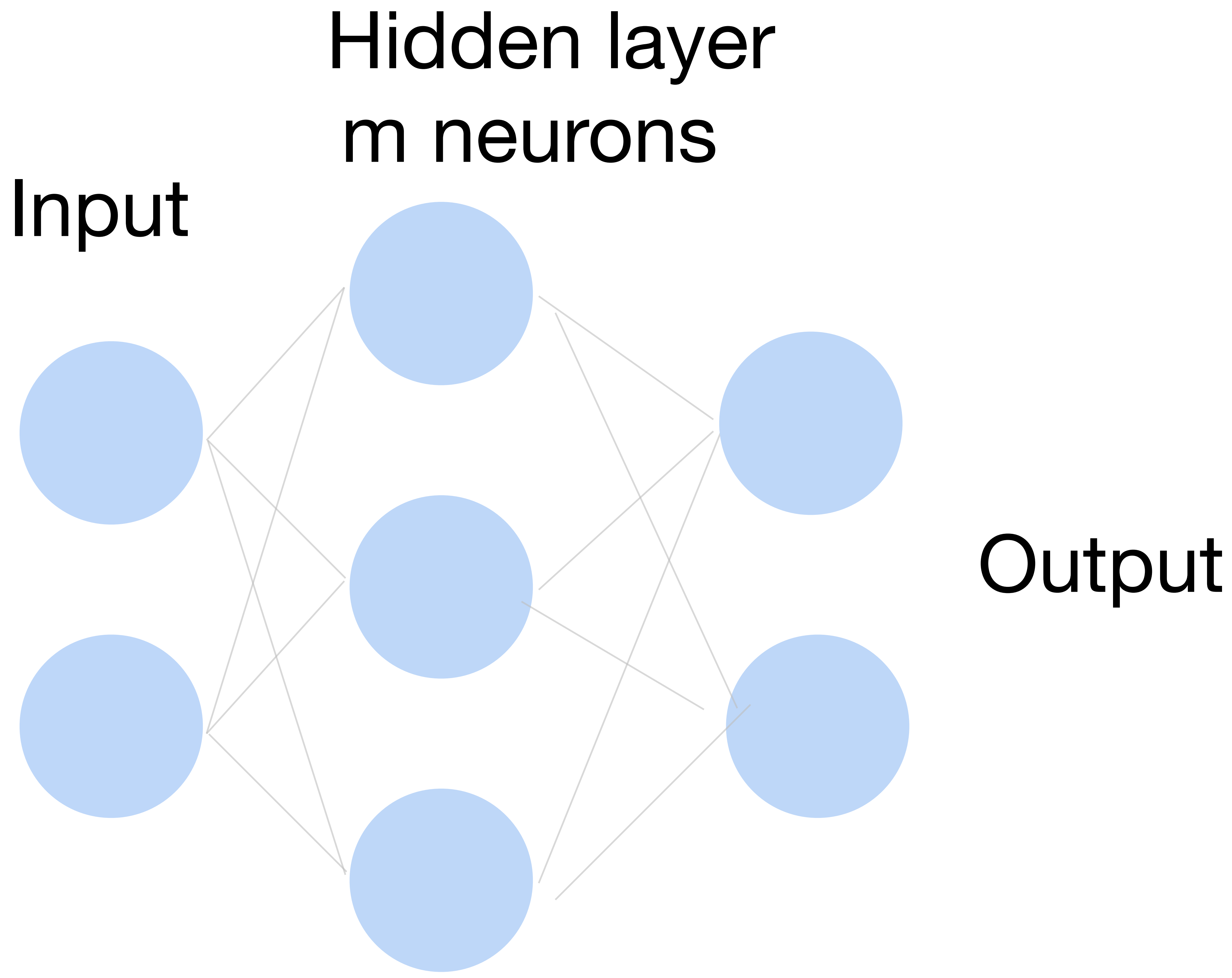


# How to train a neural network?

**Loss function:** $$\frac{1}{|D|}\sum_{i}\ell(\mathbf{x}_i, y_i)$$

**Per-sample loss:**

$$\ell(\mathbf{x}, y) = \sum_{j=1}^{K} - y_j \log p_j$$



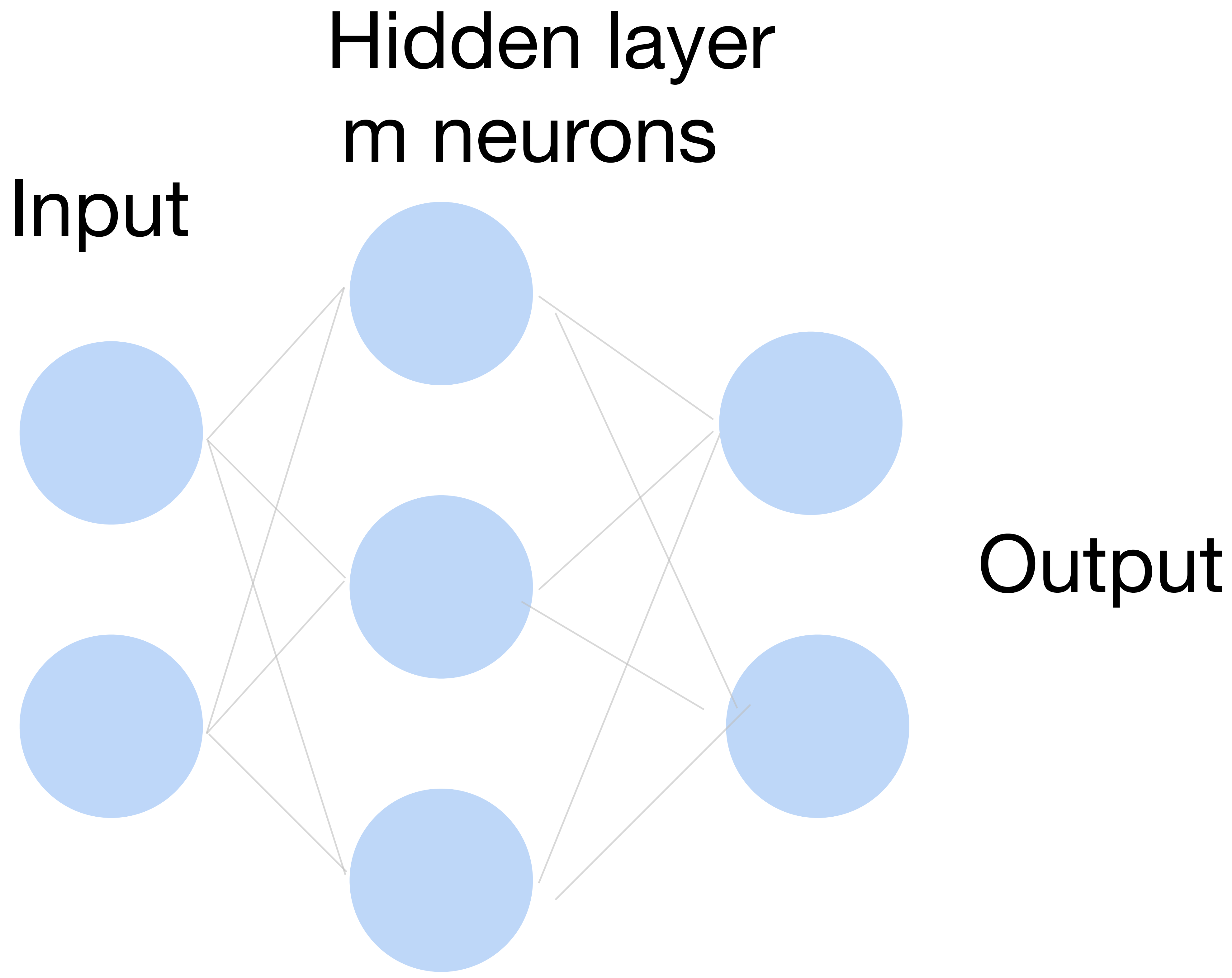
# How to train a neural network?

**Loss function:** $$\frac{1}{|D|}\sum_i \ell(\mathbf{x}_i, y_i)$$

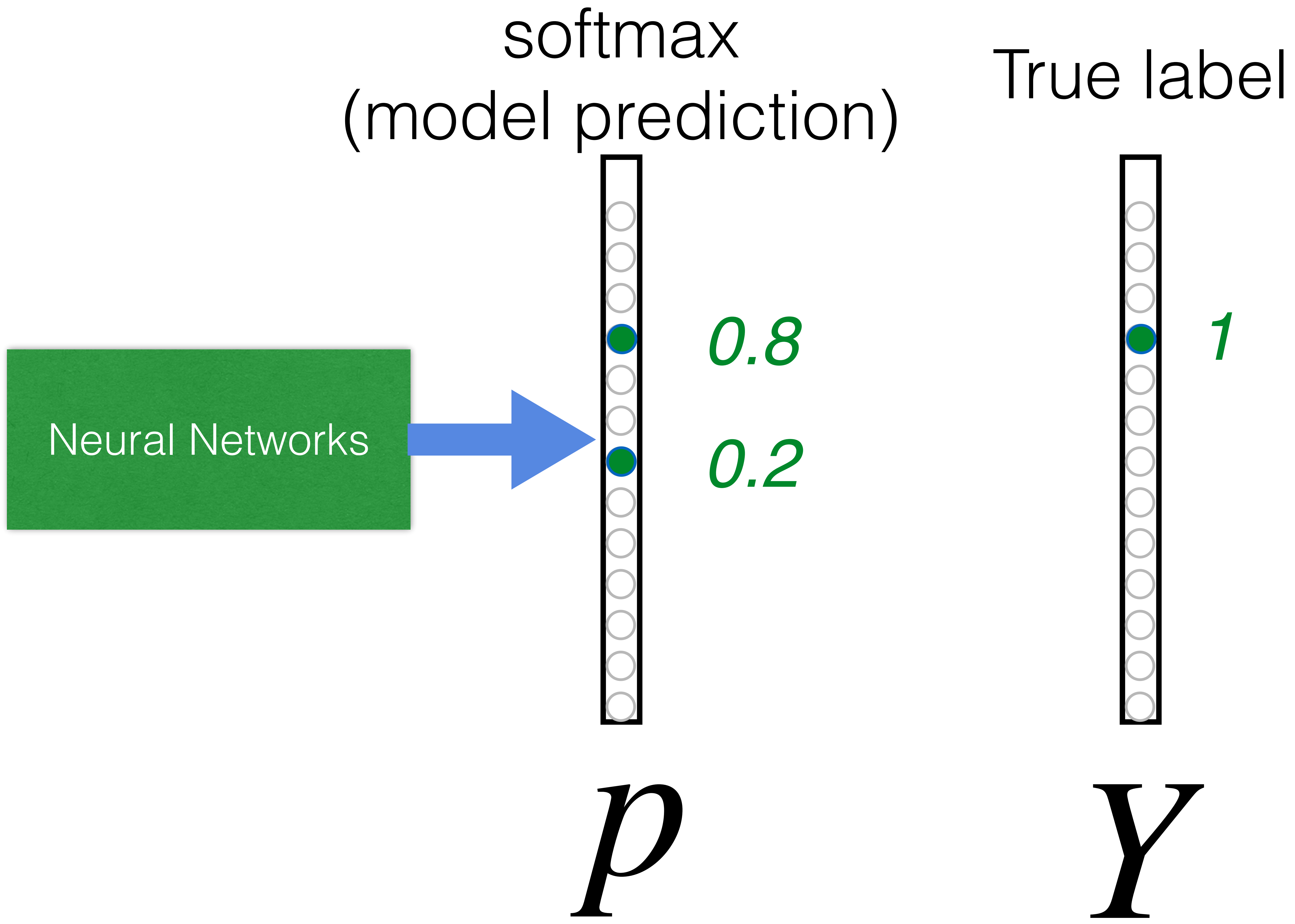
**Per-sample loss:**

$$\ell(\mathbf{x}, y) = \sum_{j=1}^{K} -y_j \log p_j$$

**Also known as cross-entropy loss or softmax loss**



# Cross-Entropy Loss




$$L_{CE} = \sum_{j} -y_j \log(p_j)$$

$$= -\log(0.8)$$

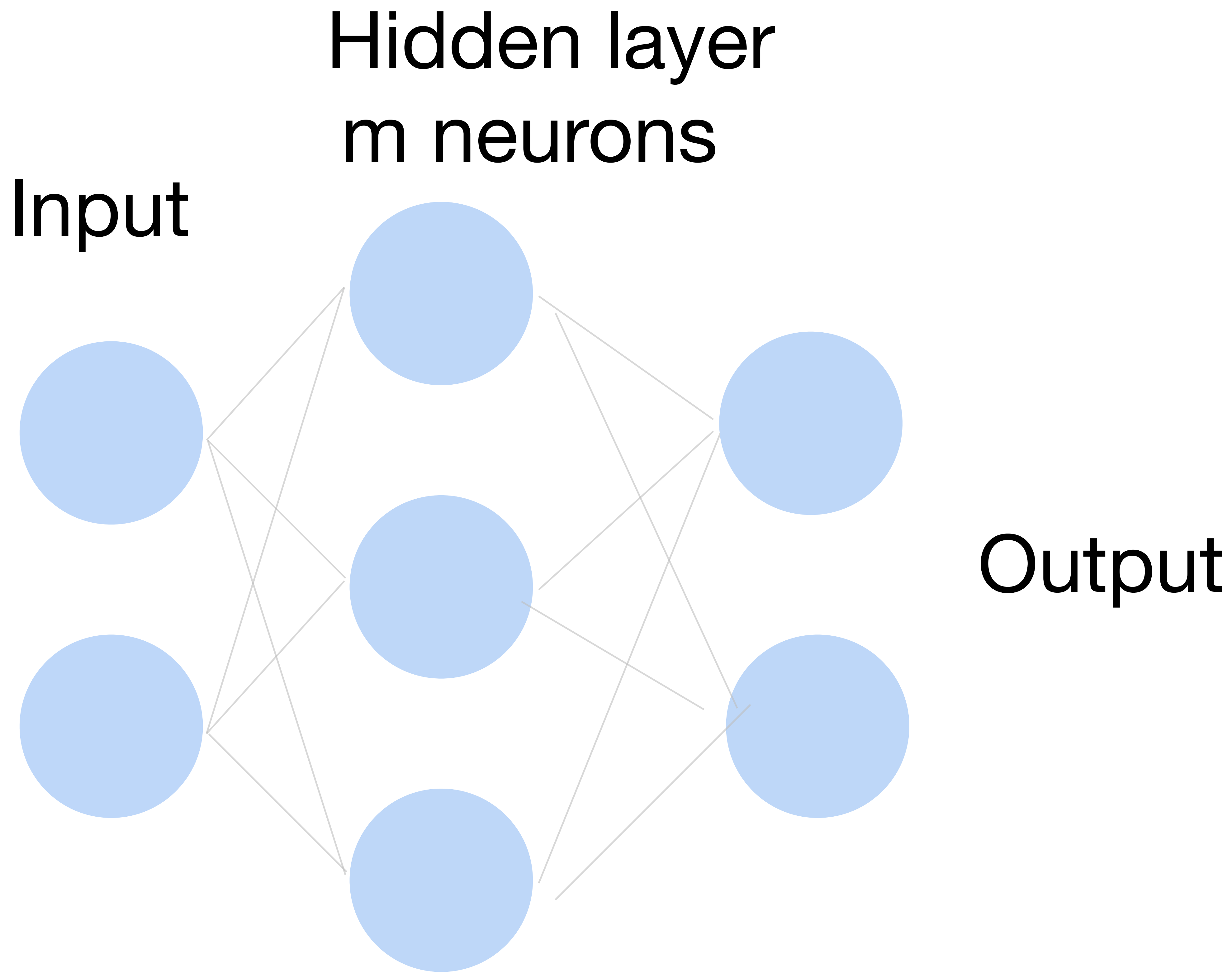
**Goal**: push **p** and **Y** to be identical

# How to train a neural network?

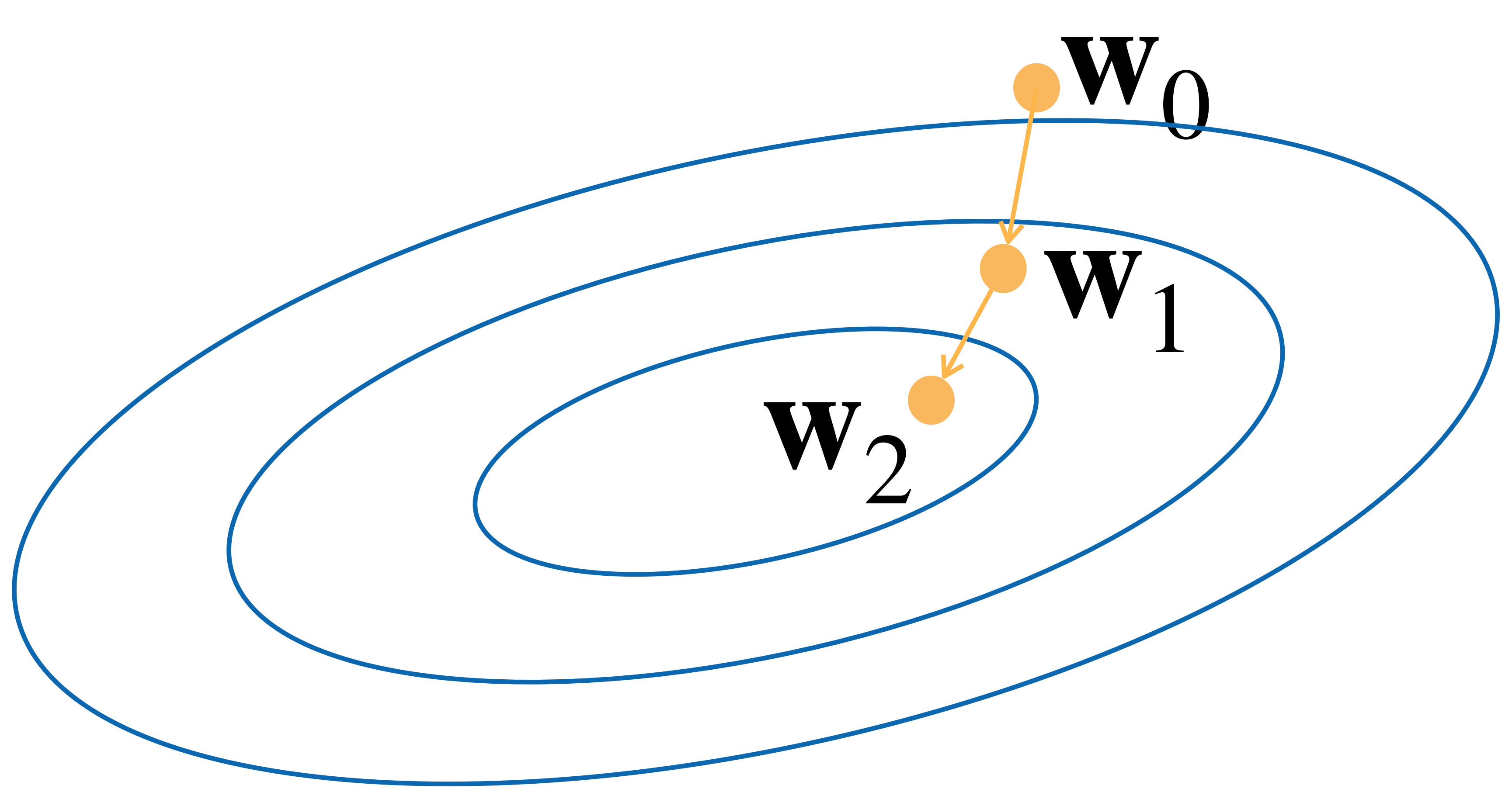
Update the weights W to minimize the loss function

$$L = \frac{1}{|D|} \sum_i \ell(\mathbf{x}_i, y_i)$$

**Use gradient descent!**



# Gradient Descent



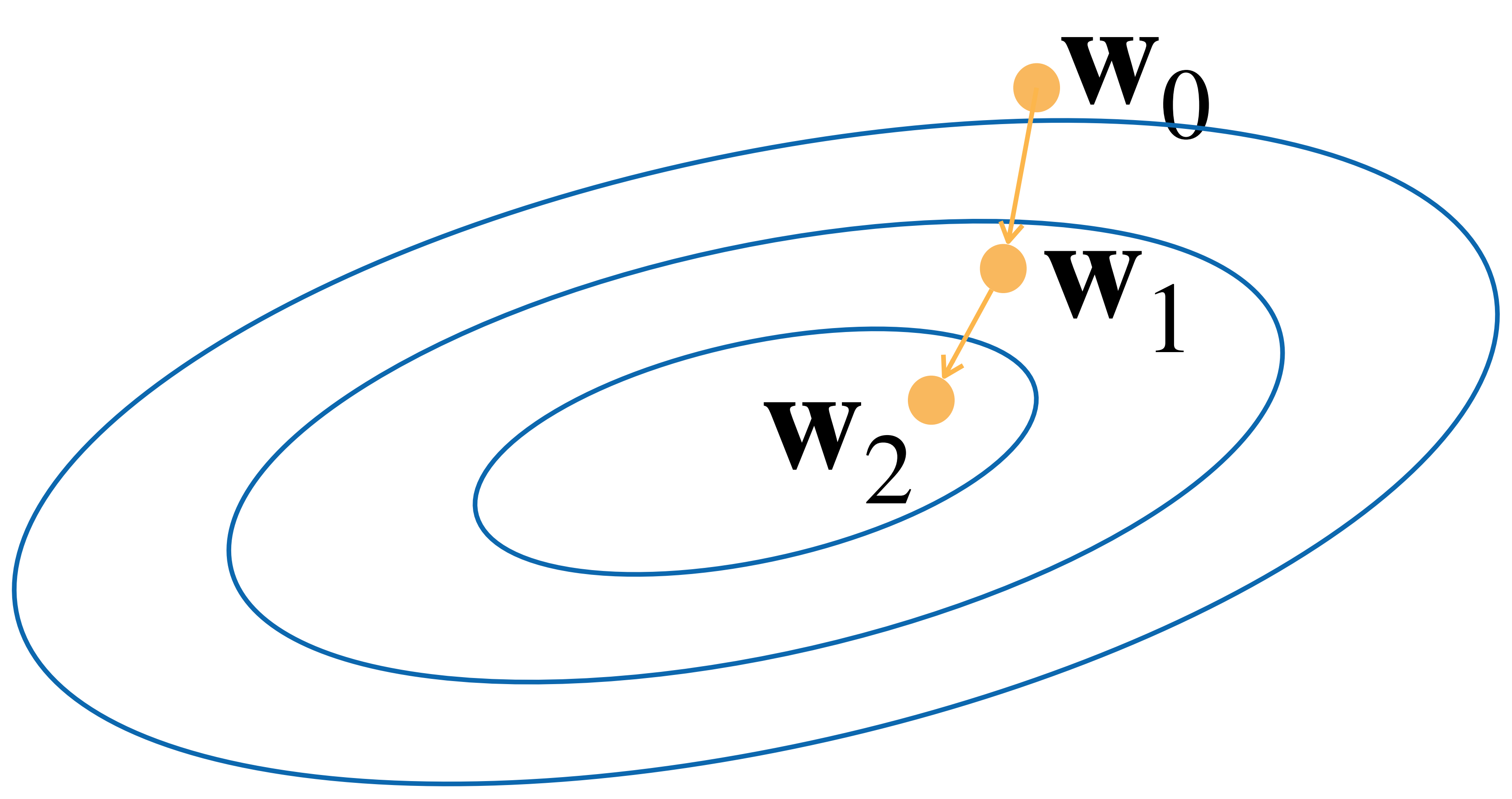

- Choose a learning rate $\alpha > 0$
- Initialize the model parameters $w_0$
- For t =1,2,…
  - Update parameters:

$$\mathbf{w}_t = \mathbf{w}_{t-1} - \alpha \frac{\partial L}{\partial \mathbf{w}_{t-1}}$$

$$= \mathbf{w}_{t-1} - \alpha \frac{1}{|D|} \sum_{\mathbf{x} \in D} \frac{\partial \ell(\mathbf{x}_i, y_i)}{\partial \mathbf{w}_{t-1}}$$

- Repeat until converges

# Gradient Descent




- Choose a learning rate $\alpha > 0$
- Initialize the model parameters $w_0$
- For t =1,2,…
  - Update parameters:

$$\mathbf{w}_t = \mathbf{w}_{t-1} - \alpha \frac{\partial L}{\partial \mathbf{w}_{t-1}}$$

$$= \mathbf{w}_{t-1} - \alpha \frac{1}{|D|} \sum_{\mathbf{x} \in D} \frac{\partial \ell(\mathbf{x}_i, y_i)}{\partial \mathbf{w}_{t-1}}$$

D can
be very large.
Expensive

- Repeat until converges

# Minibatch Stochastic Gradient Descent

- Choose a learning rate $\alpha > 0$
- Initialize the model parameters $w_0$
- For t =1,2,…
  - **Randomly sample a subset (mini-batch)** $B \subset D$
    Update parameters:

$$\mathbf{w}_t = \mathbf{w}_{t-1} - \alpha \frac{1}{|B|} \sum_{\mathbf{x} \in B} \frac{\partial \ell(\mathbf{x}_i, y_i)}{\partial \mathbf{w}_{t-1}}$$

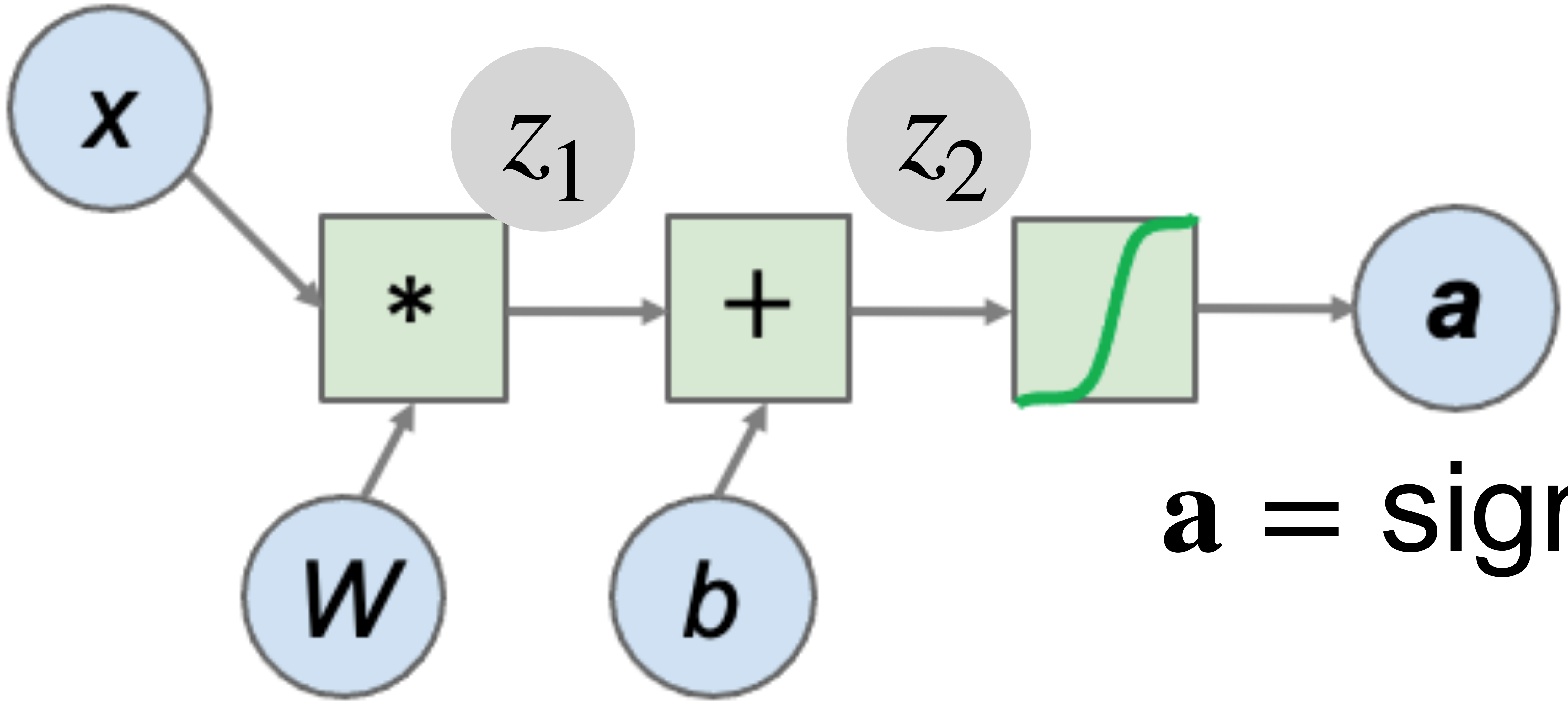
- Repeat

# Calculate gradient: backpropagation with chain rule

- Define a loss function L
- Gradient with respect to a variable =

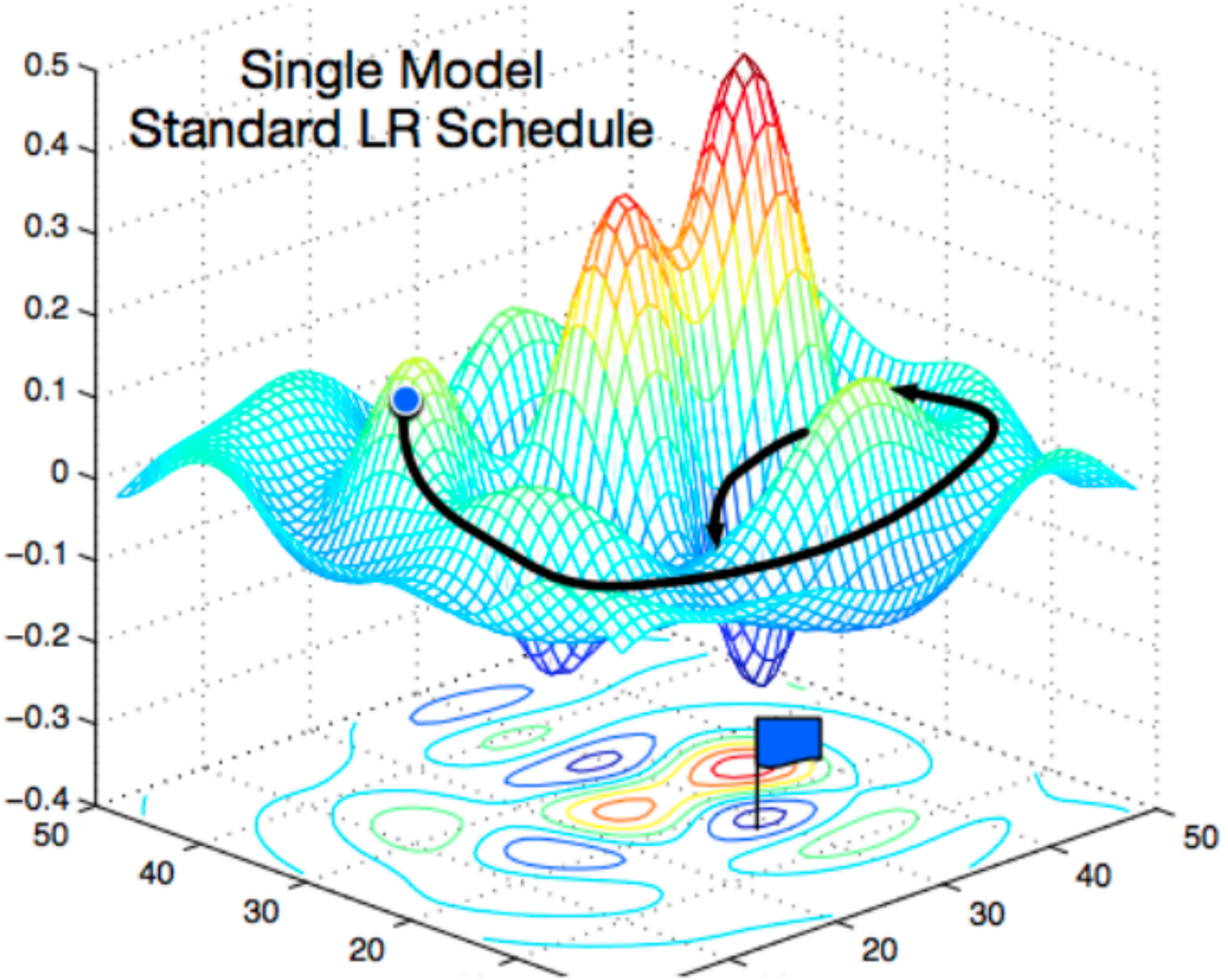
gradient of the top x gradient from the current operation

$$\frac{\partial L}{\partial \boldsymbol{W}} = \frac{\partial L}{\partial \boldsymbol{z_1}} \frac{\partial \boldsymbol{z_1}}{\partial \boldsymbol{W}}$$




$$\mathbf{a} = \text{sigmoid}(\mathbf{Wx} + \mathbf{b})$$

# Non-convex Optimization

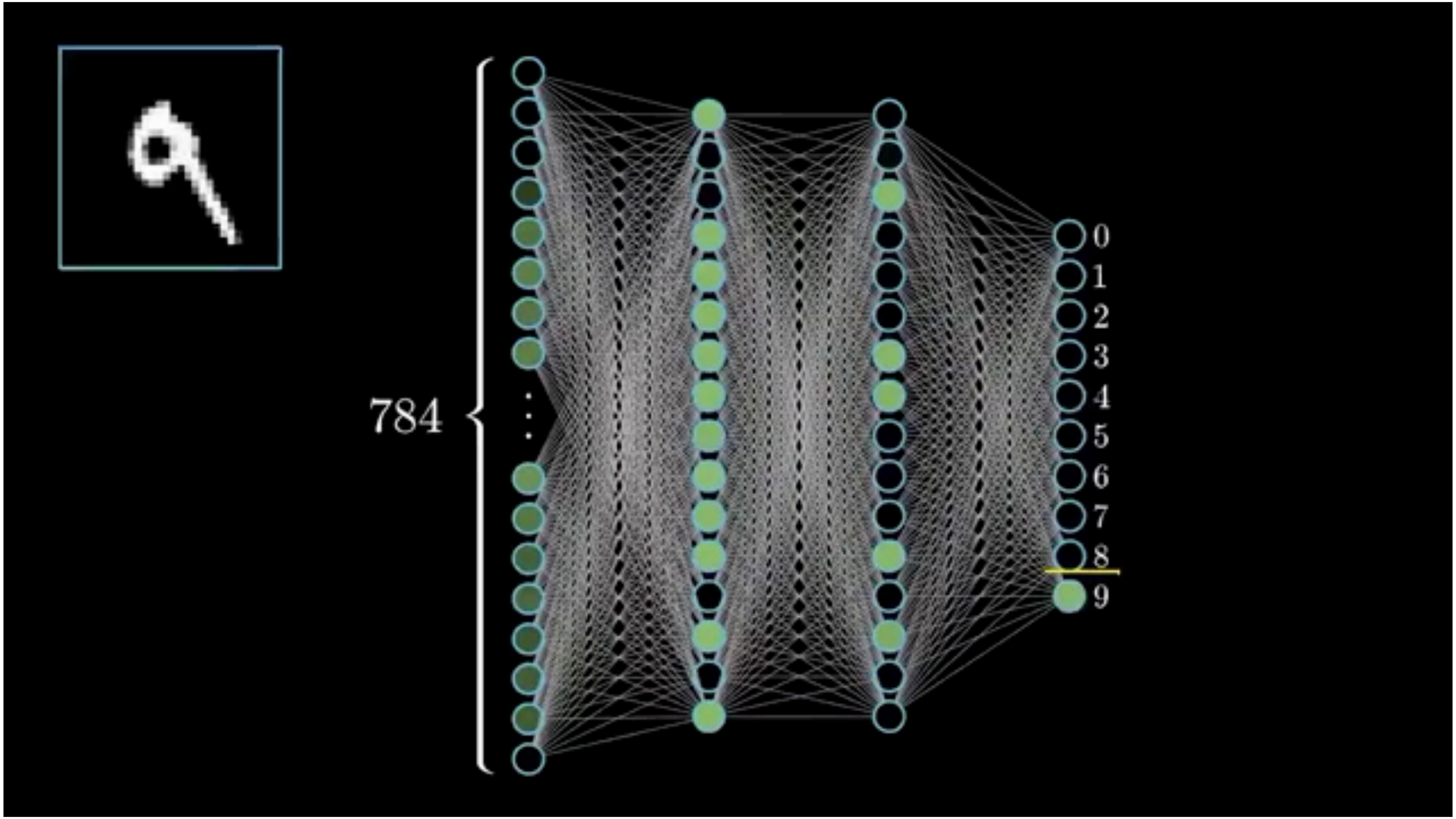



[Gao and Li et al., 2018]

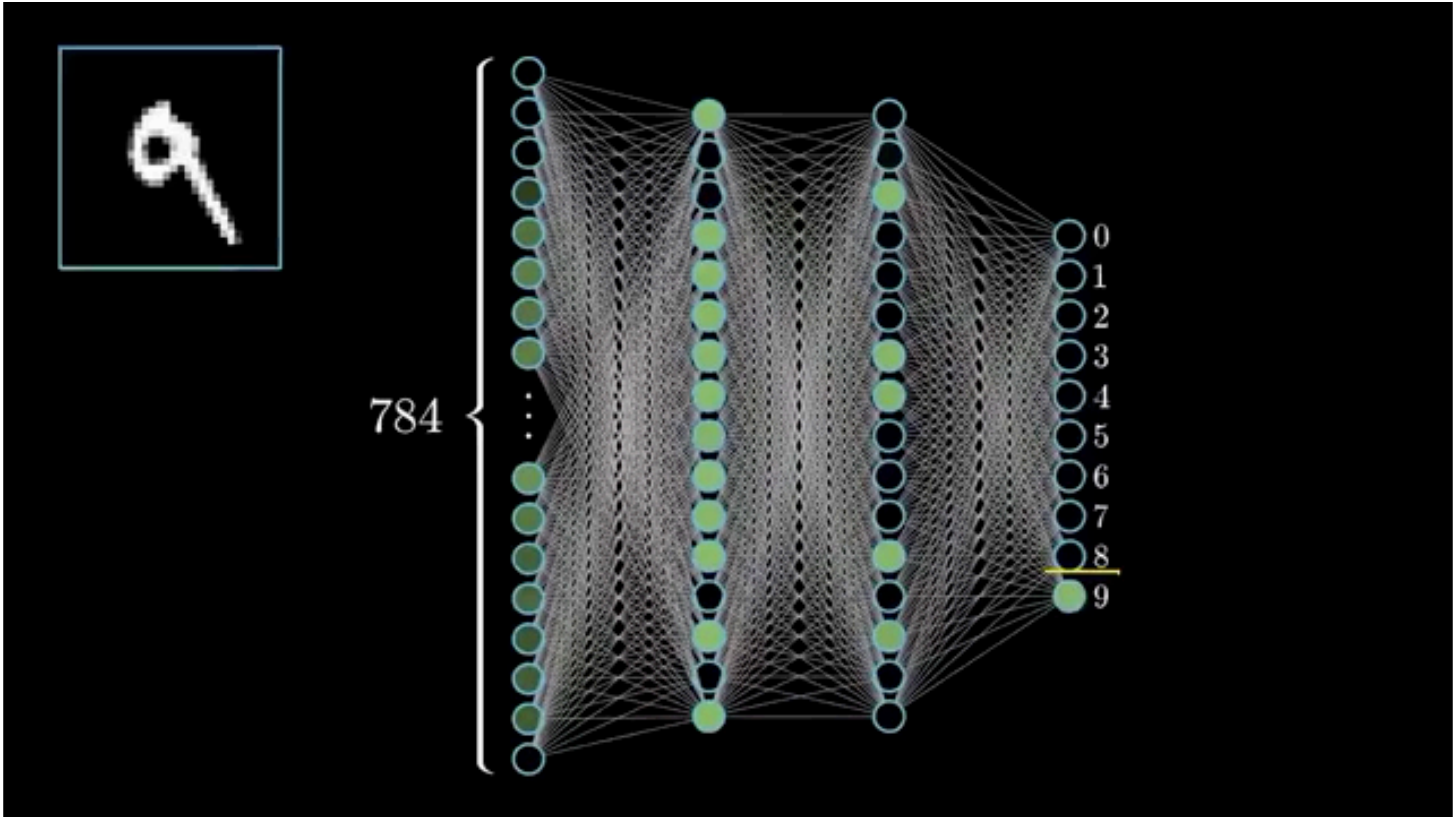
# Using SGD in PyTorch (code demo)

https://colab.research.google.com/github/pytorch/tutorials/blob/gh-pages/_downloads/17a7c7cb80916fcdf921097825a0f562/cifar10_tutorial.ipynb#scrollTo=9eTWywELV7kr

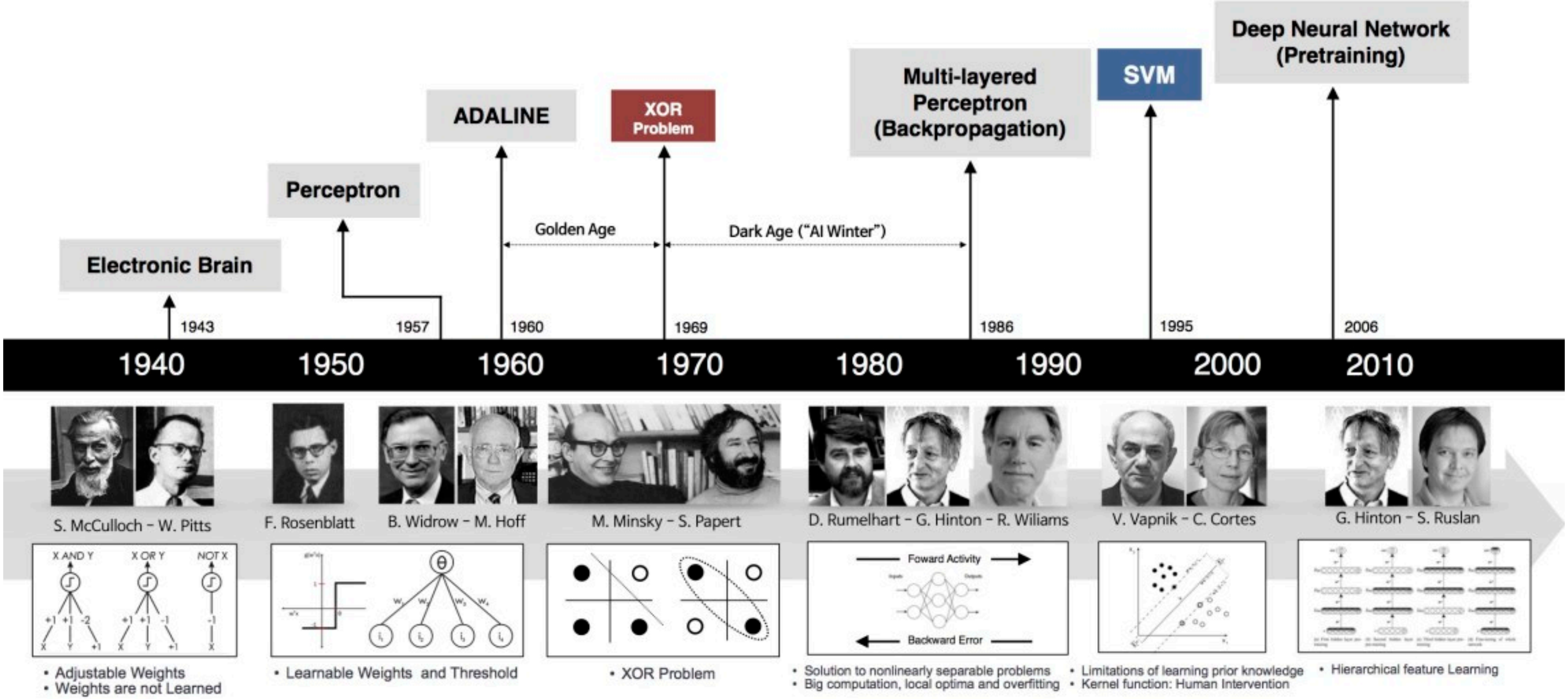
# Classify MNIST handwritten digits (HW6)



# Classify MNIST handwritten digits (HW6)



# Brief history of neural networks



# How to classify

## Cats vs. dogs?

# How to classify
## Cats vs. dogs?

Dual
12MP
wide-angle and
telephoto cameras

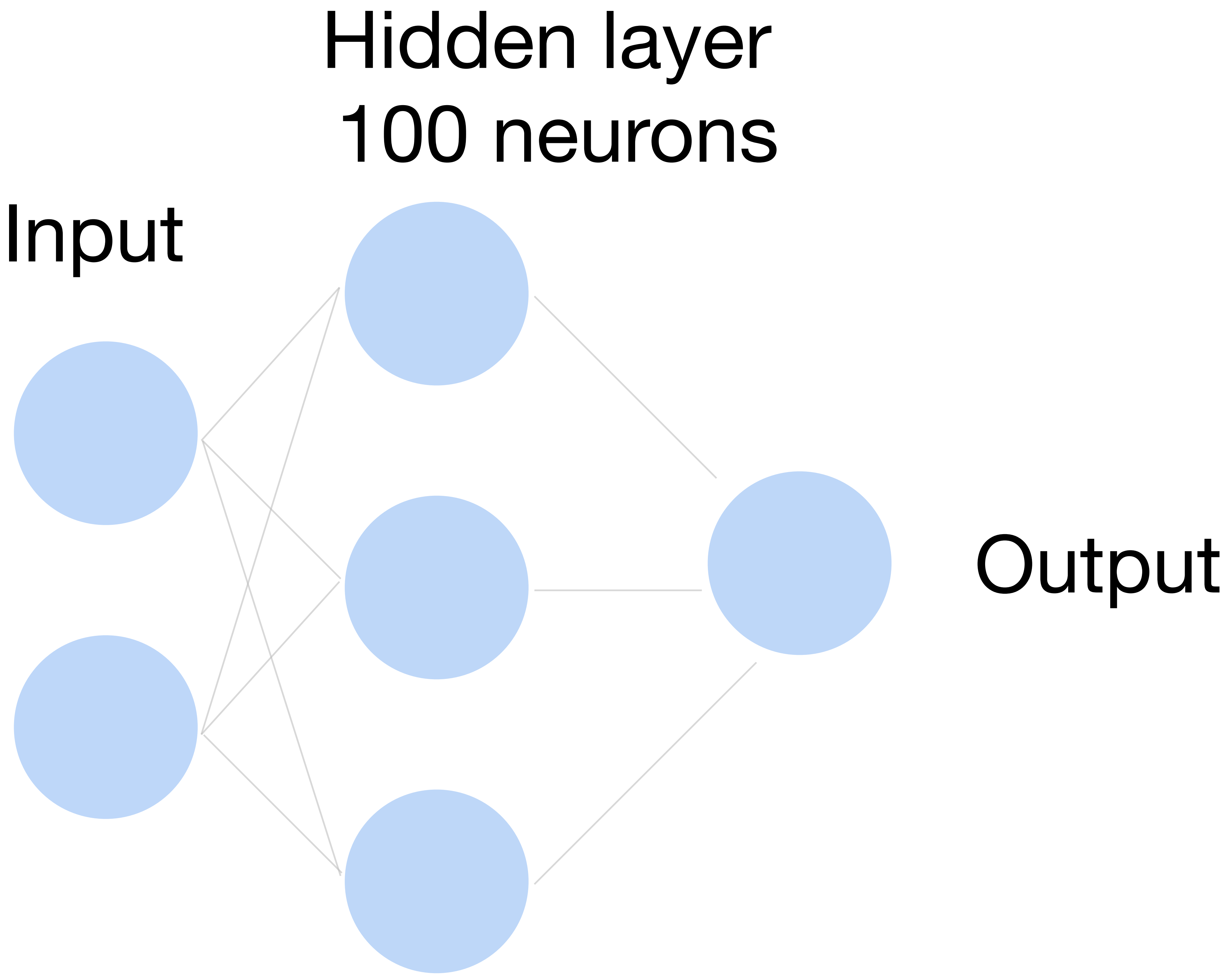
**36M** floats in a RGB image!

# Fully Connected Networks

**Cats vs. dogs?**

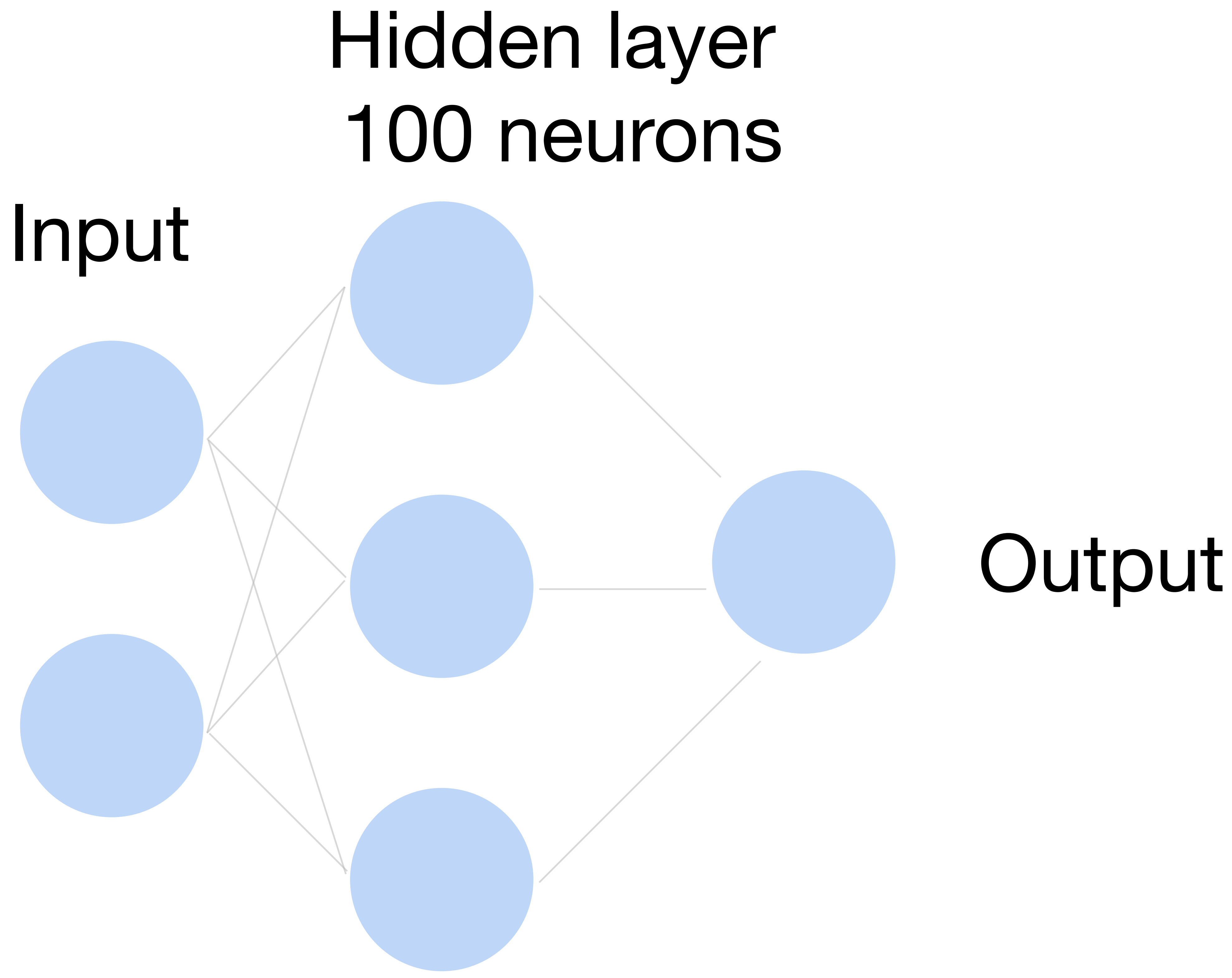
# Fully Connected Networks

**Cats vs. dogs?**



# Fully Connected Networks

**Cats vs. dogs?**




~ 36M elements x 100 = ~**3.6B** parameters!

# Convolutions come to rescue!

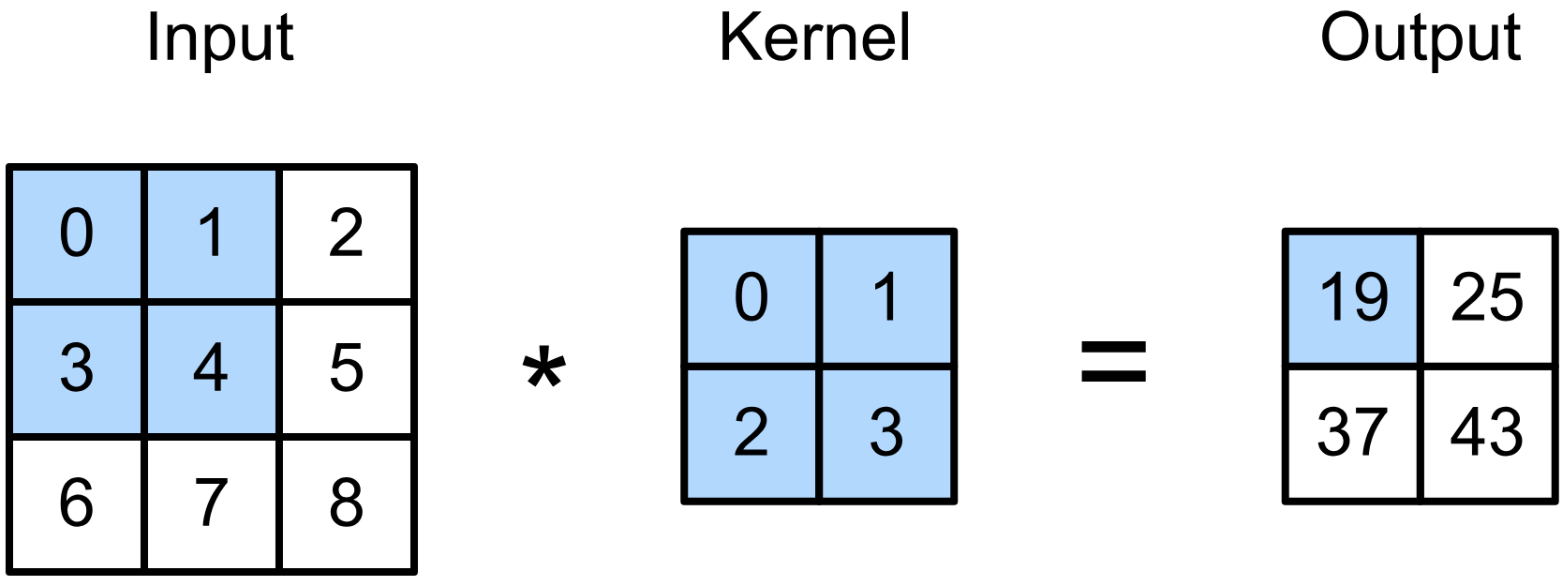
Where is Waldo?

## Why Convolution?

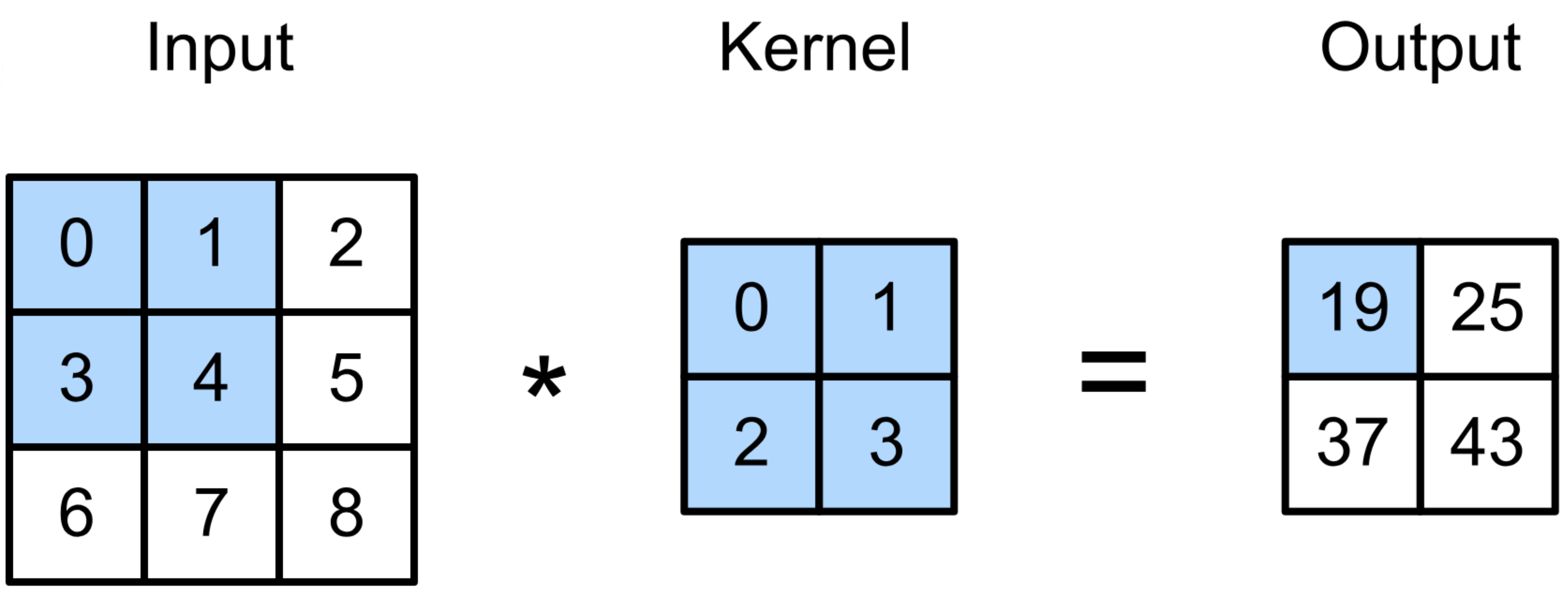
- Translation Invariance
- Locality

# 2-D Convolution

# 2-D Convolution

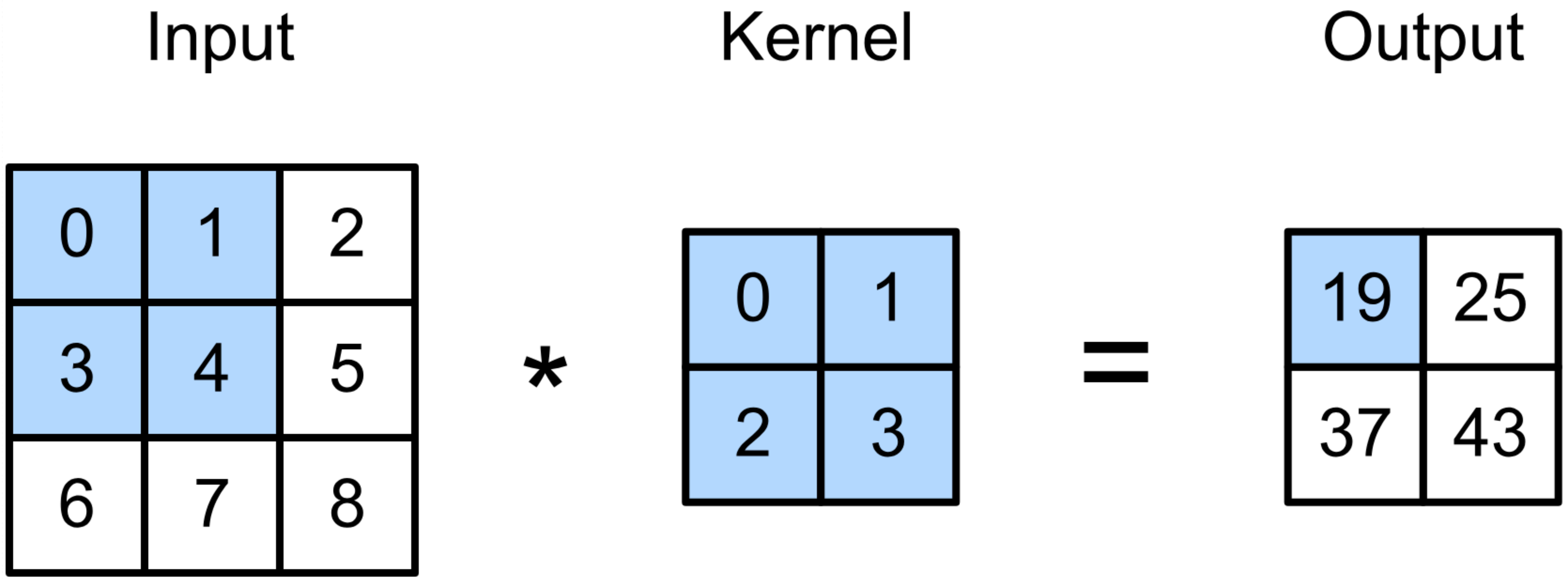


# 2-D Convolution

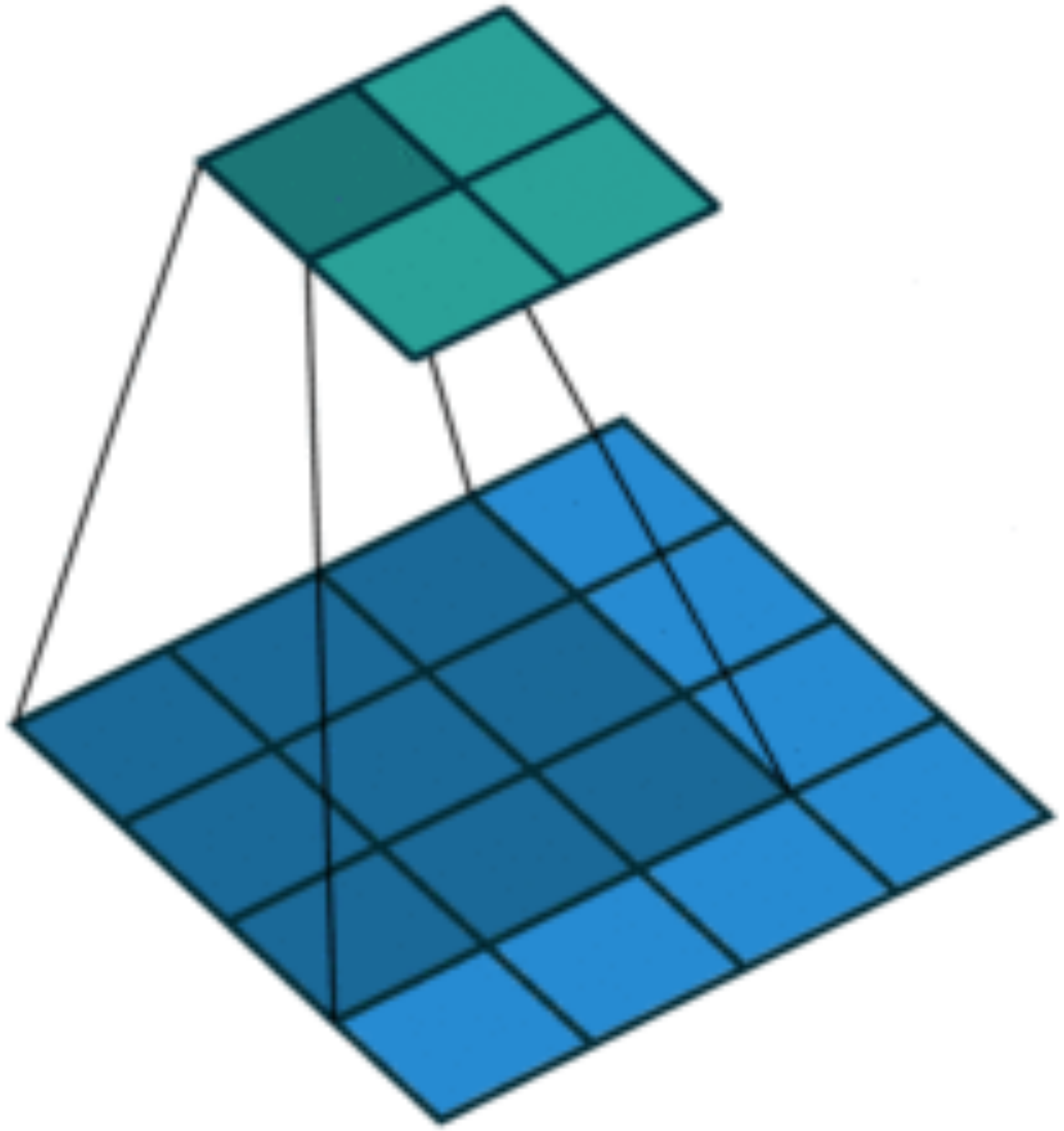



$$0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 = 19,$$
$$1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 = 25,$$
$$3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 = 37,$$
$$4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 = 43.$$

# 2-D Convolution

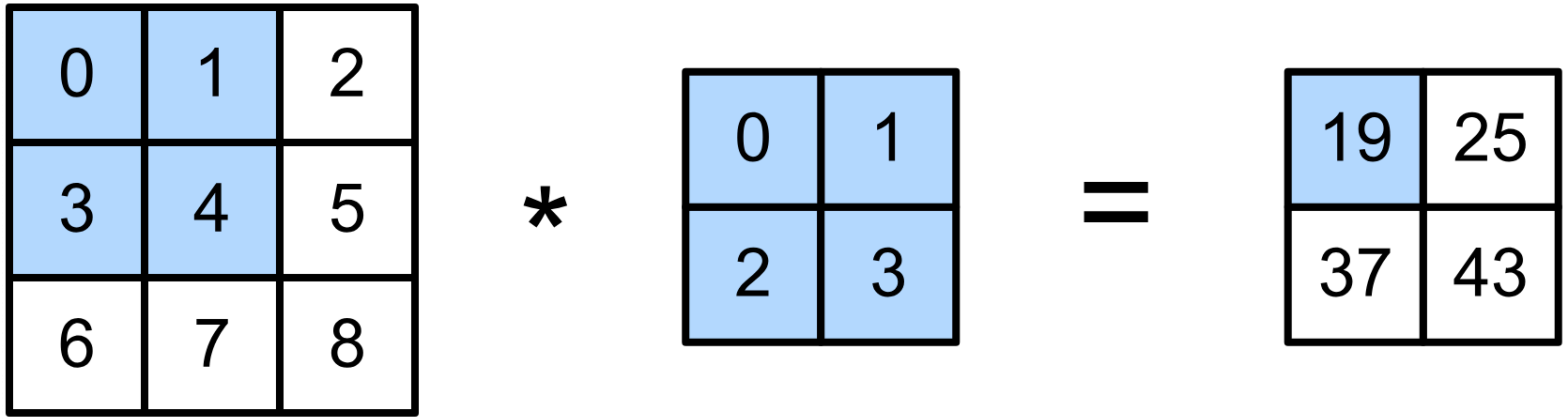



$$0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 = 19,$$
$$1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 = 25,$$
$$3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 = 37,$$
$$4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 = 43.$$



(vdumoulin@ Github)

# 2-D Convolution Layer



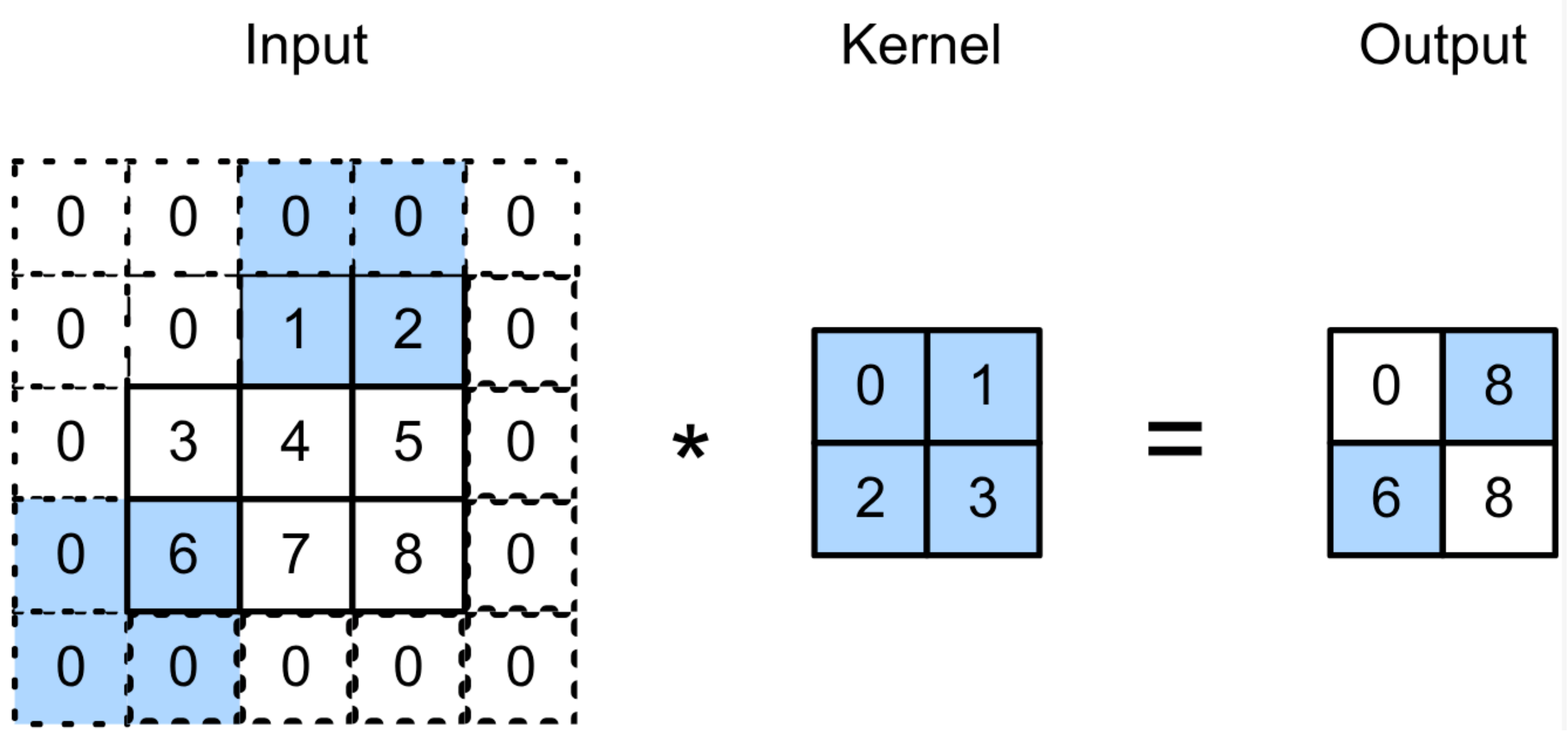

- $\mathbf{X} : n_h \times n_w$ input matrix
- $\mathbf{W} : k_h \times k_w$ kernel matrix
- b: scalar bias
- $\mathbf{Y} : (n_h - k_h + 1) \times (n_w - k_w + 1)$ output matrix

$$\mathbf{Y} = \mathbf{X} \star \mathbf{W} + b$$

- **W** and *b* are learnable parameters

# 2-D Convolution Layer with Stride and Padding

- Stride is the #rows/#columns per slide
- Padding adds rows/columns around input
- Output shape



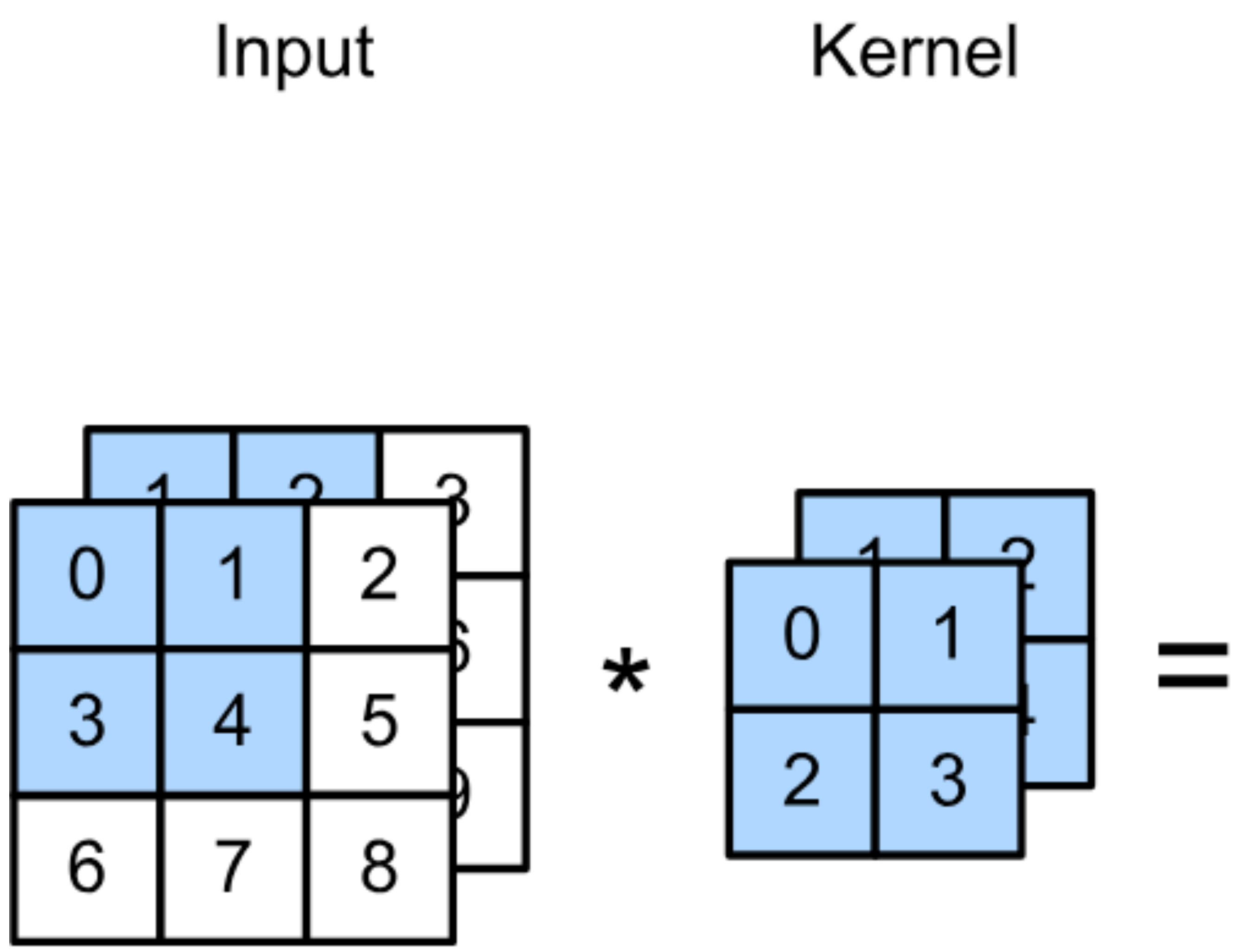

**Kernel/filter size**

$$\lfloor (n_h - k_h + p_h + s_h)/s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w)/s_w \rfloor$$

**Input size** **Pad** **Stride**

# Multiple Input Channels

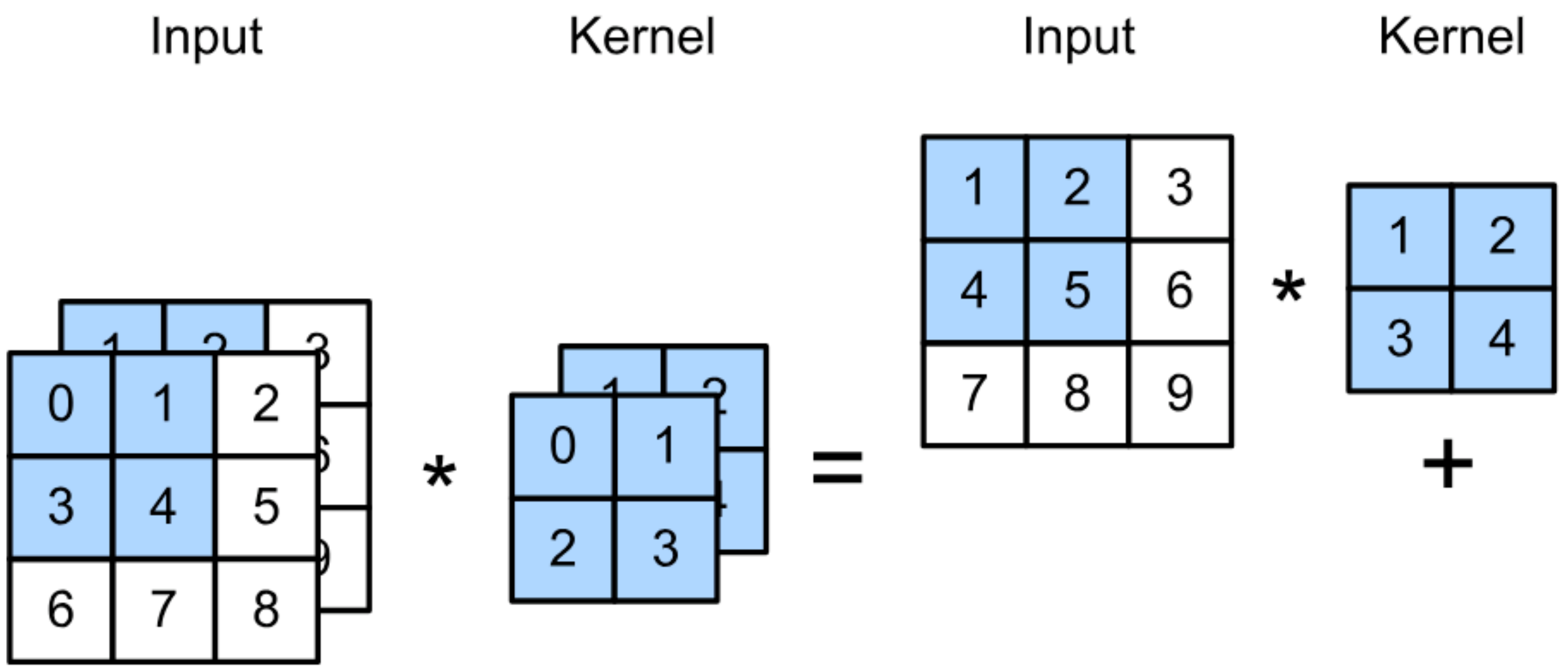
- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels




)

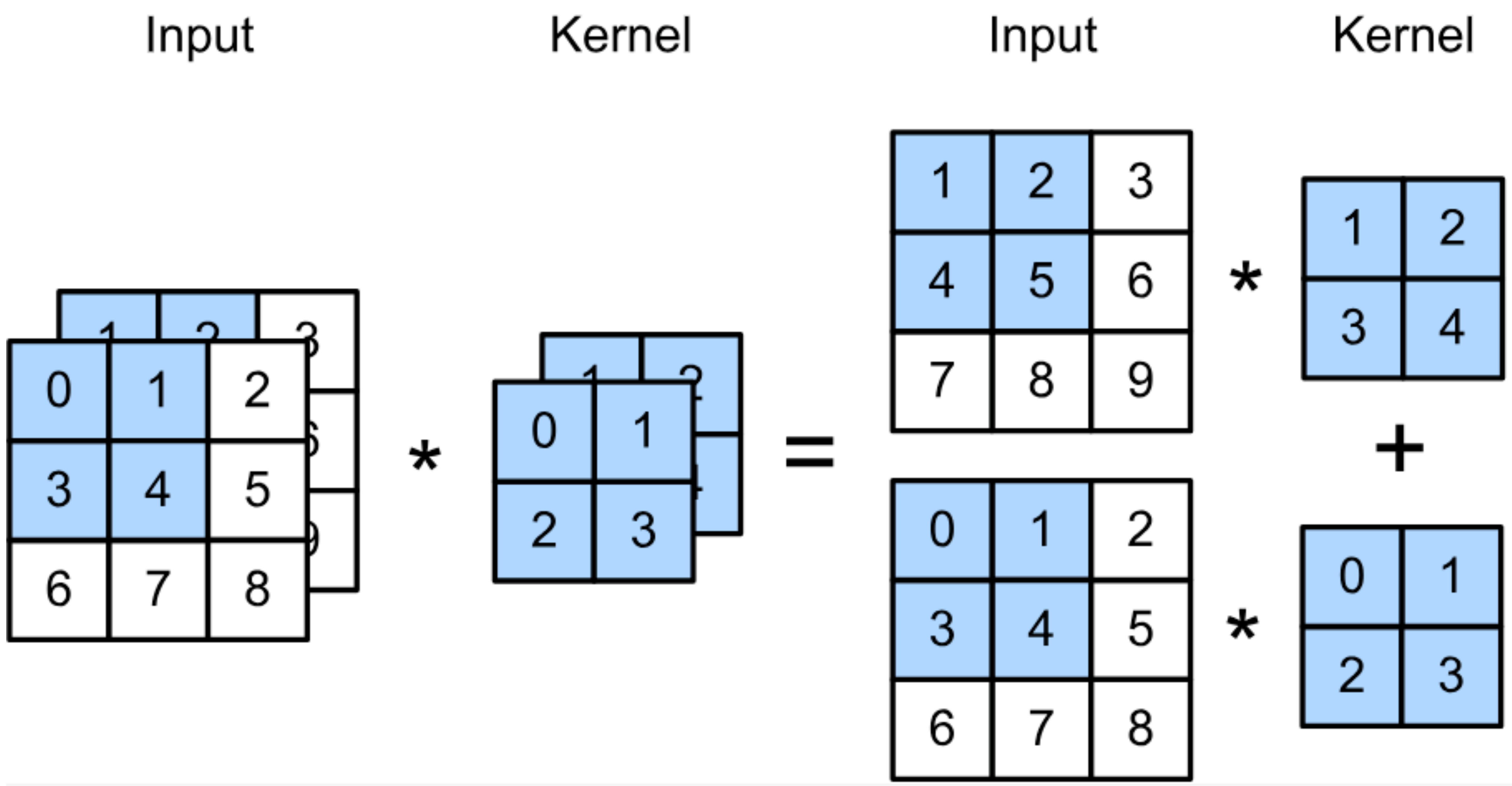
# Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels



# Multiple Input Channels

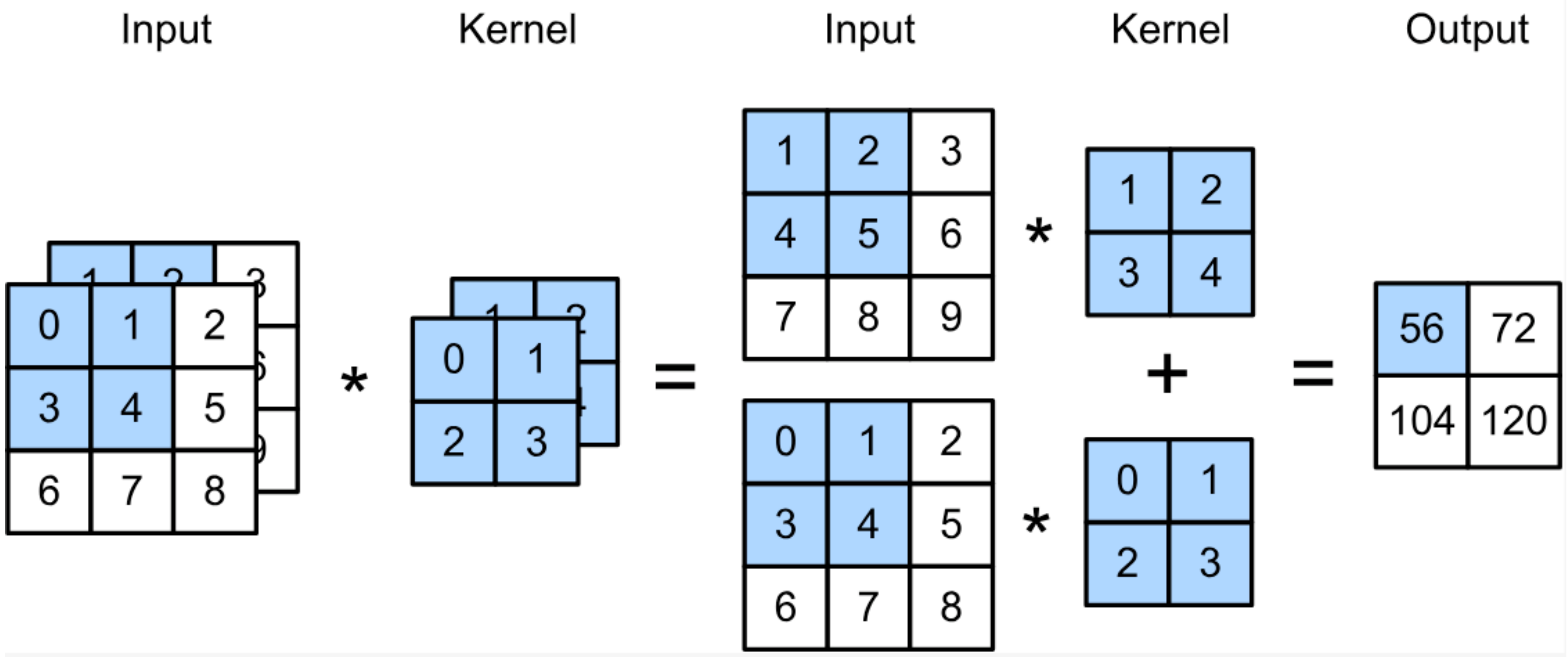
- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels




)

# Multiple Input Channels

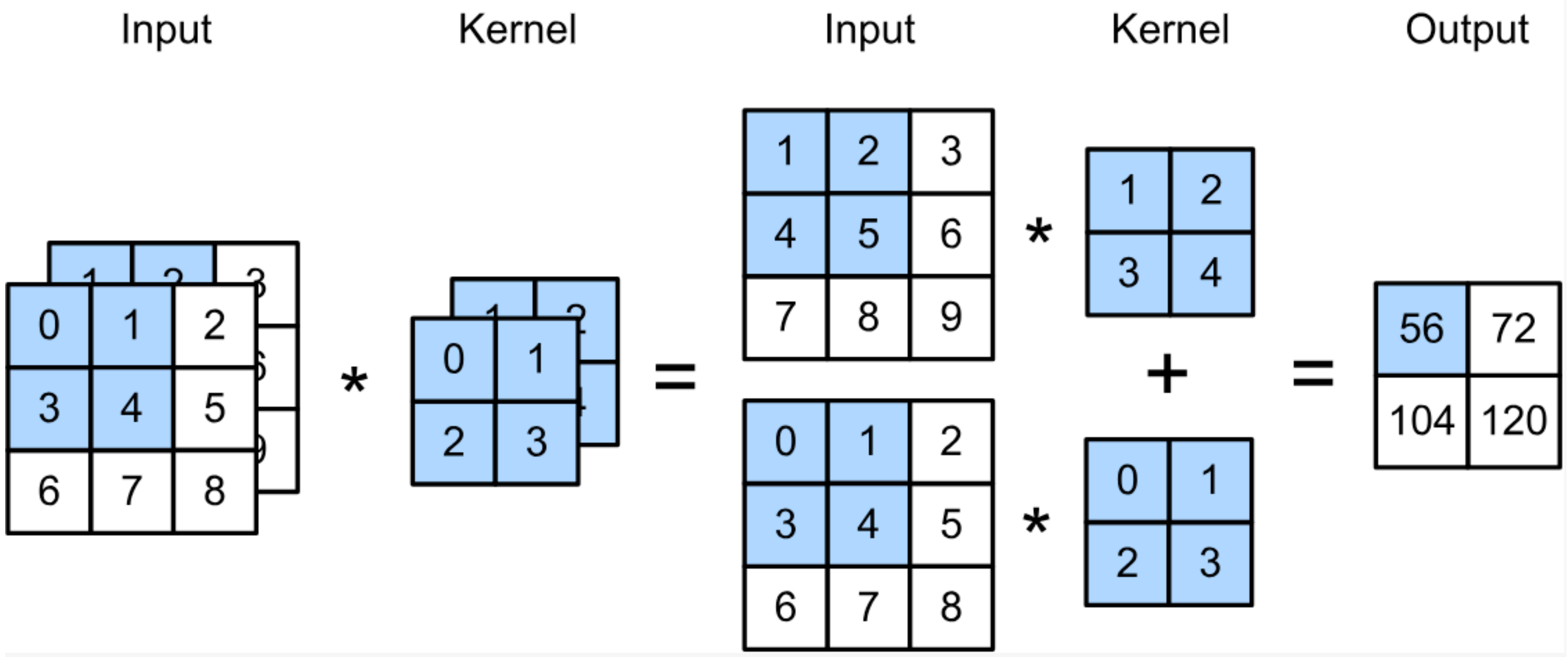
- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels




)

# Multiple Input Channels

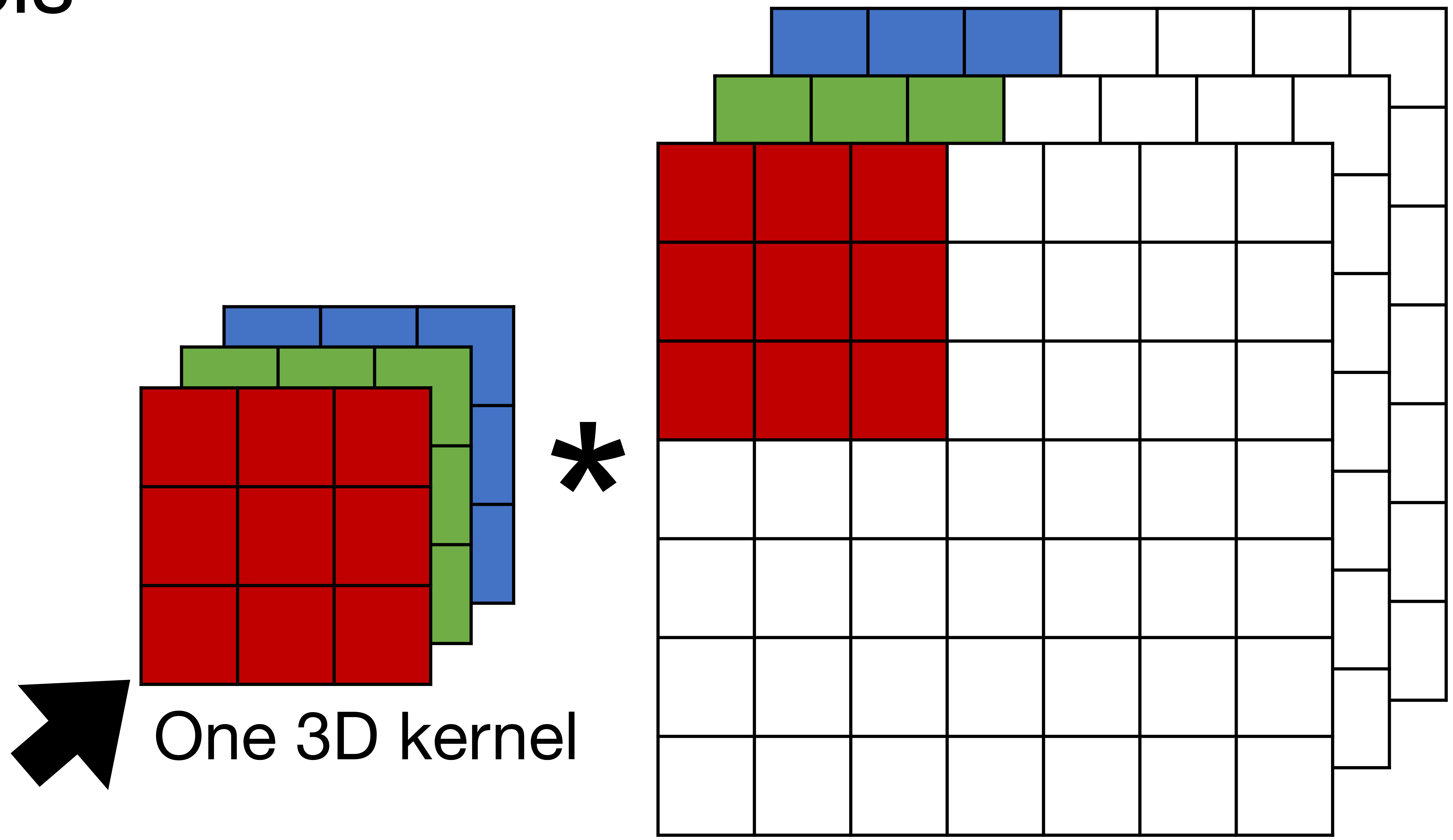
- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels




$$(1 \times 1 + 2 \times 2 + 4 \times 3 + 5 \times 4)$$
$$+(0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3)$$
$$= 56$$

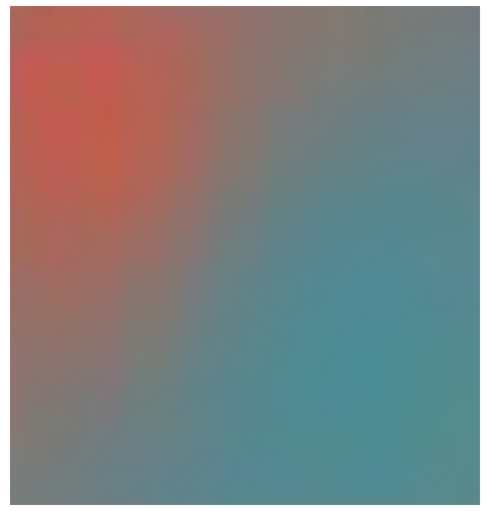
# Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a 2D kernel for each channel, and then sum results over channels



# Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Also call each 3D kernel a “**filter**”, which produce only **one** output channel (due to summation over channels)



One filter
(3 channels)

*

RGB (3 input channels)

# Multiple filters (in one layer)

- Apply multiple filters on the input
- Each filter may learn different features about the input
- Each filter (3D kernel) produces one output channel

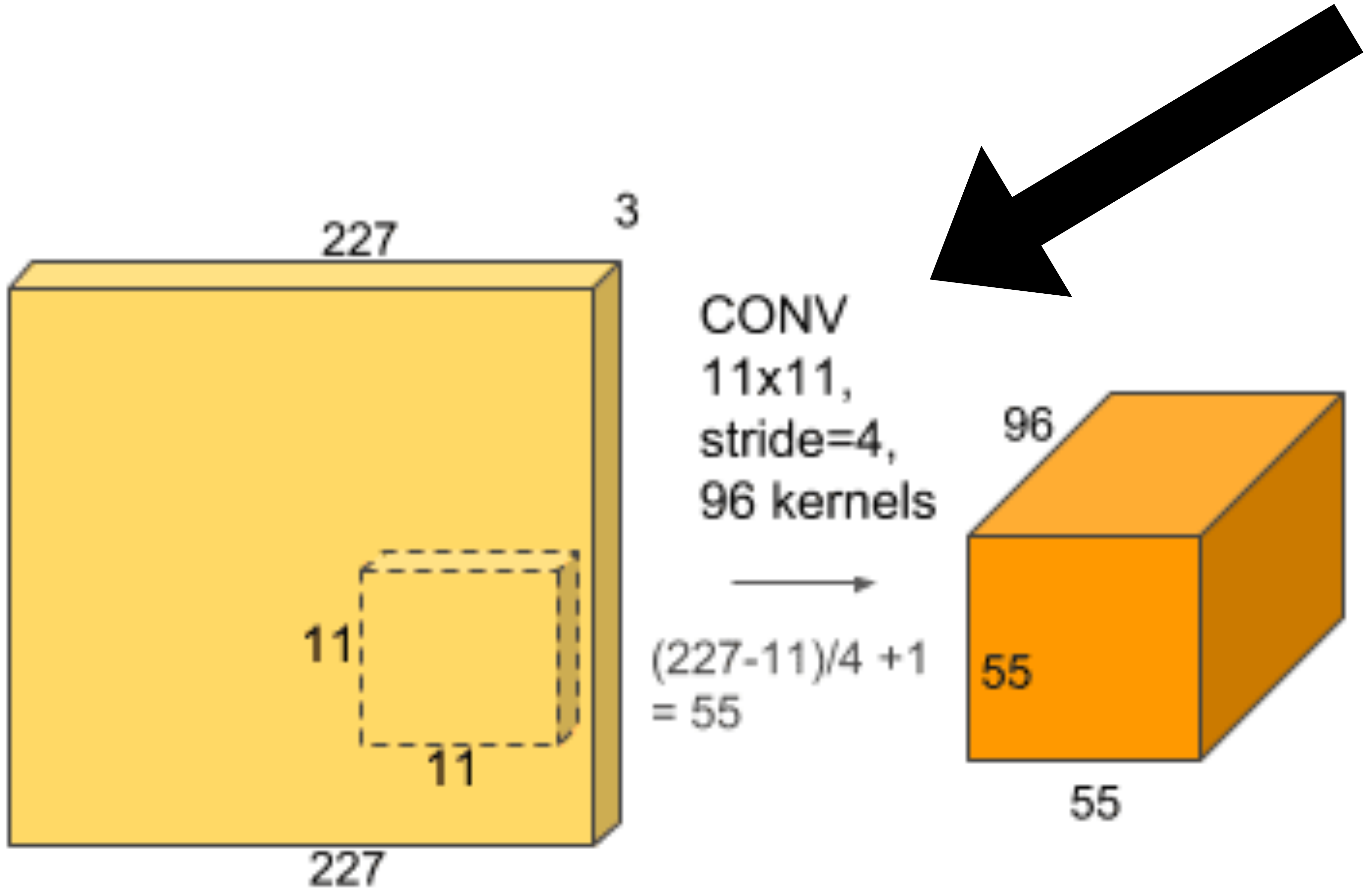
A different filter

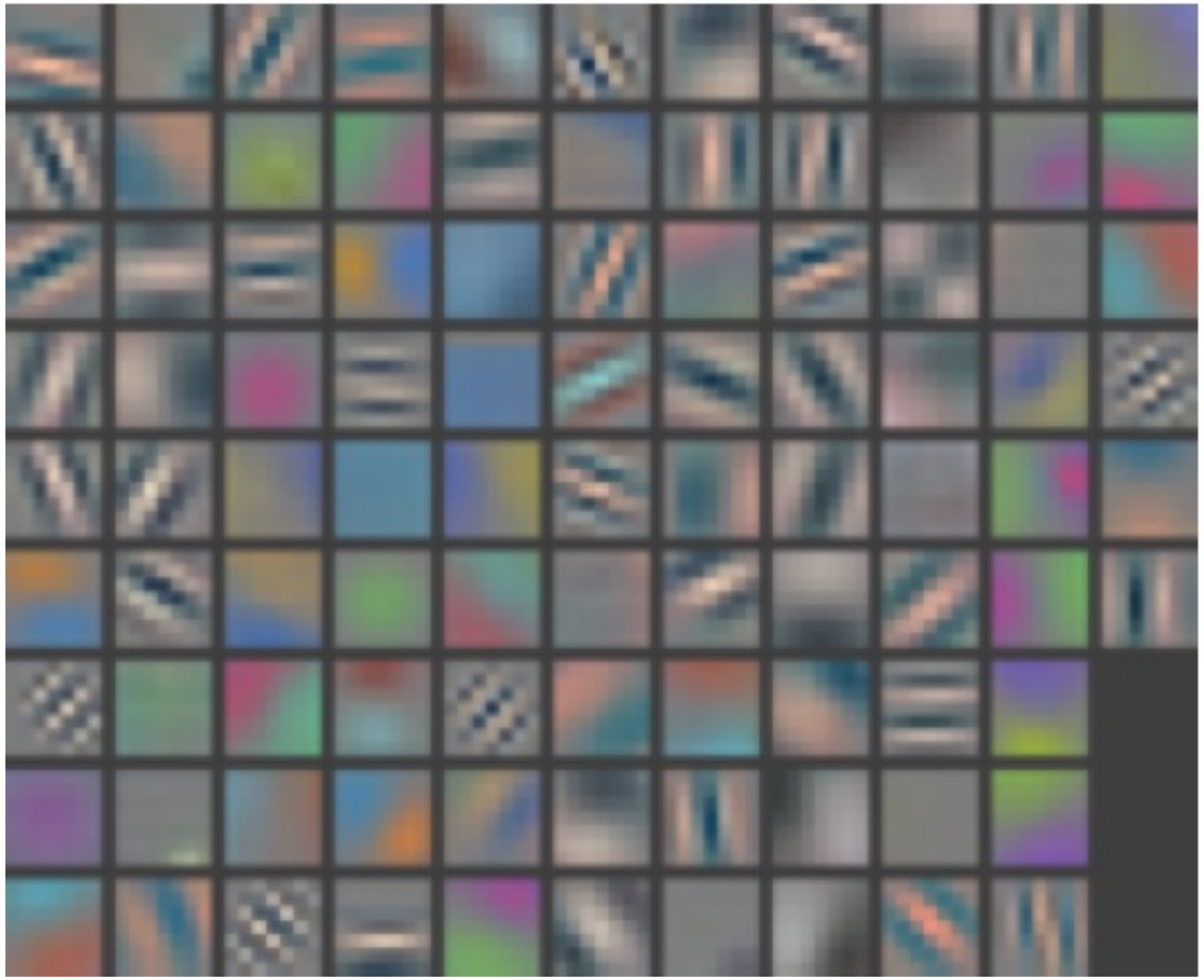
*

RGB (3 input channels)

# Conv1 Filters in AlexNet

- 96 filters (each of size 11x11x3)
- Gabor filters



Figures from Visualizing and Understanding Convolutional Networks
by *M. Zeiler and R. Fergus*

# Multiple Output Channels

- The # of output channels = # of filters
- Input $\mathbf{X} : c_i \times n_h \times n_w$
- Kernel $\mathbf{W} : c_o \times c_i \times k_h \times k_w$
- Output $\mathbf{Y} : c_o \times m_h \times m_w$

$$\mathbf{Y}_{i,:,:} = \mathbf{X} \star \mathbf{W}_{i,:,:,:}$$

for $i = 1, \ldots, c_o$

# Multiple Output Channels

- The # of output channels = # of filters
- Input $\mathbf{X} : c_i \times n_h \times n_w$
- Kernel $\mathbf{W} : c_o \times c_i \times k_h \times k_w$
- Output $\mathbf{Y} : c_o \times m_h \times m_w$

$$\mathbf{Y}_{i,:,:} = \mathbf{X} \star \mathbf{W}_{i,:,:,:}$$

for $i = 1, \ldots, c_o$

# Multiple Output Channels

- The # of output channels = # of filters
- Input $\mathbf{X} : c_i \times n_h \times n_w$
- Kernel $\mathbf{W} : c_o \times c_i \times k_h \times k_w$
- Output $\mathbf{Y} : c_o \times m_h \times m_w$

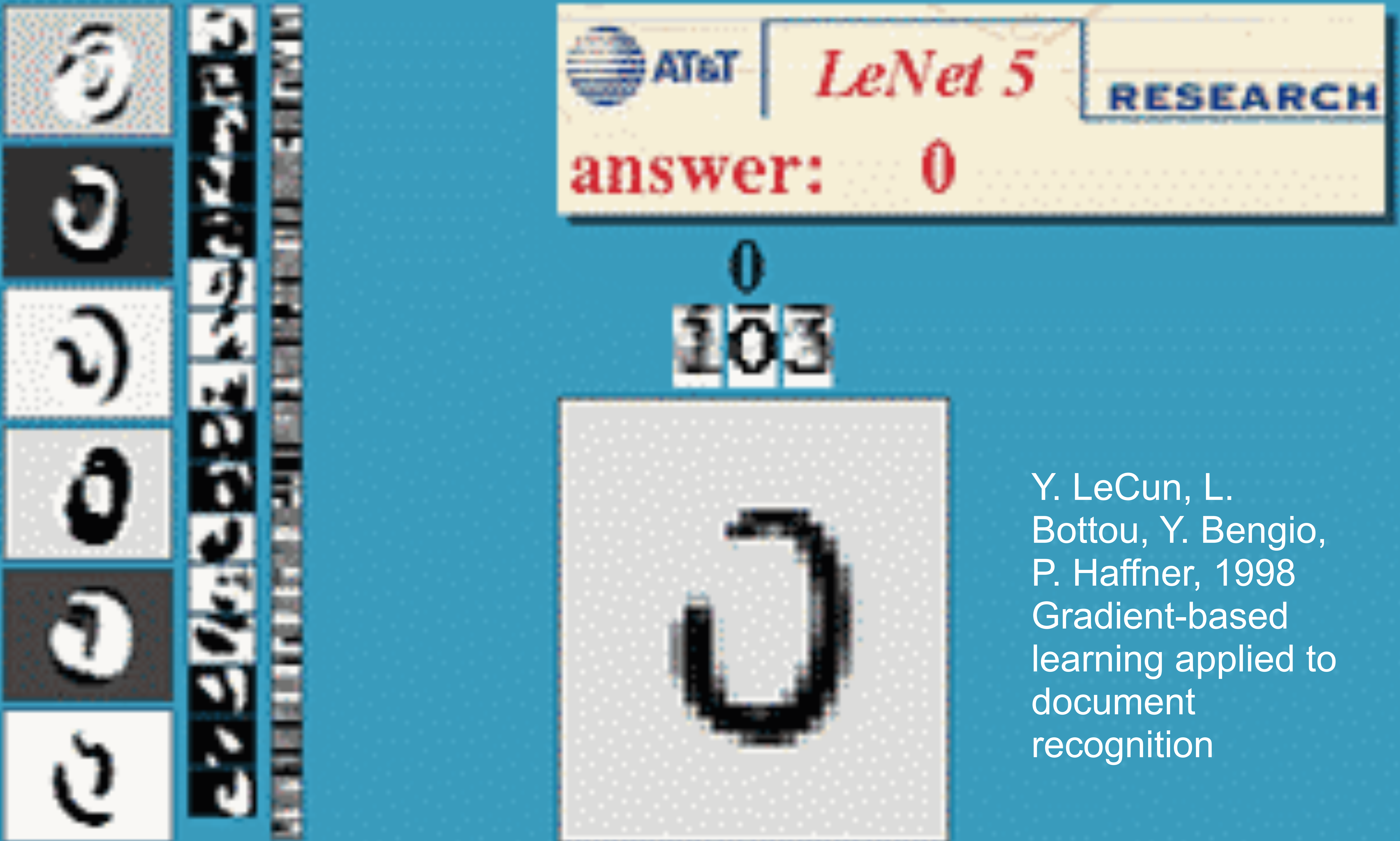
$$\mathbf{Y}_{i,:,:} = \mathbf{X} \star \mathbf{W}_{i,:,:,:}$$

for $i = 1, \ldots, c_o$

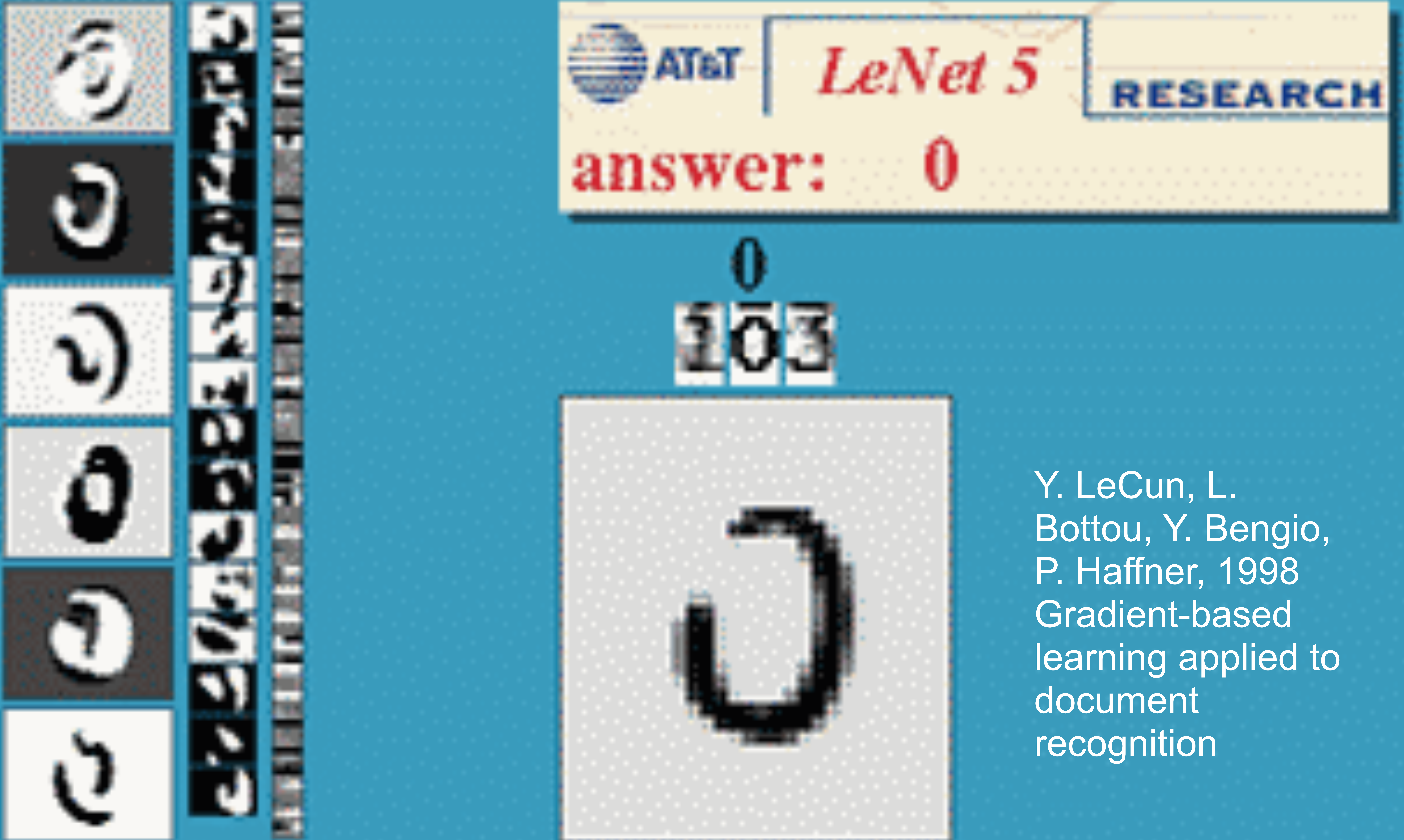
# Convolutional Neural Networks

# LeNet Architecture


gluon-cv.mxnet.io




Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition




Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition

# LeNet in Pytorch (HW7)

## Connect theory and practice

```
def __init__(self):
    super(LeNet5, self).__init__()
    # Convolution (In LeNet-5, 32x32 images are given as input. Hence padding of 2 is done below)
    self.conv1 = torch.nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1, padding=2, bias=True)
    # Max-pooling
    self.max_pool_1 = torch.nn.MaxPool2d(kernel_size=2)
    # Convolution
    self.conv2 = torch.nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5, stride=1, padding=0, bias=True)
    # Max-pooling
    self.max_pool_2 = torch.nn.MaxPool2d(kernel_size=2)
    # Fully connected layer
    self.fc1 = torch.nn.Linear(16*5*5, 120)   # convert matrix with 16*5*5 (= 400) features to a matrix of 120 features (col
    self.fc2 = torch.nn.Linear(120, 84)       # convert matrix with 120 features to a matrix of 84 features (columns)
    self.fc3 = torch.nn.Linear(84, 10)        # convert matrix with 84 features to a matrix of 10 features (columns)
```

# Quiz break

Which one of the following is NOT true?

A. LeNet has two convolutional layers

B. The first convolutional layer in LeNet has 5x5x6x3 parameters, in case of RGB input

C. Pooling is performed right after convolution

D. Pooling layer does not have learnable parameters

# Quiz break

Which one of the following is NOT true?

A. LeNet has two convolutional layers

B. The first convolutional layer in LeNet has 5x5x6x3 parameters, in case of RGB input

C. Pooling is performed right after convolution

D. Pooling layer does not have learnable parameters

Pooling is performed after ReLU: conv->relu->pooling

# Quiz break

You have a kernel (filter) and a given image. What filter map (output) is obtained from applying the kernel to the image without padding and zero bias?

| | | |
|---|---|---|
| **3** | **2** | **1** |
| **3** | 3 | 1 |
| **1** | 2 | 1 |

Image

| | |
|---|---|
| **1** | **2** |
| **2** | 1 |

Kernel

# Quiz break

You have a kernel (filter) and a given image. What filter map (output) is obtained from applying the kernel to the image without padding and zero bias?

| | | |
|---|---|---|
| **3** | **2** | **1** |
| **3** | 3 | 1 |
| **1** | 2 | 1 |

Image

| | |
|---|---|
| **1** | **2** |
| **2** | 1 |

Kernel

3*1 + 2*2 + 3*2 + 3*1 = 16

2*1 + 1*2 + 3*2 + 1*1 = 11

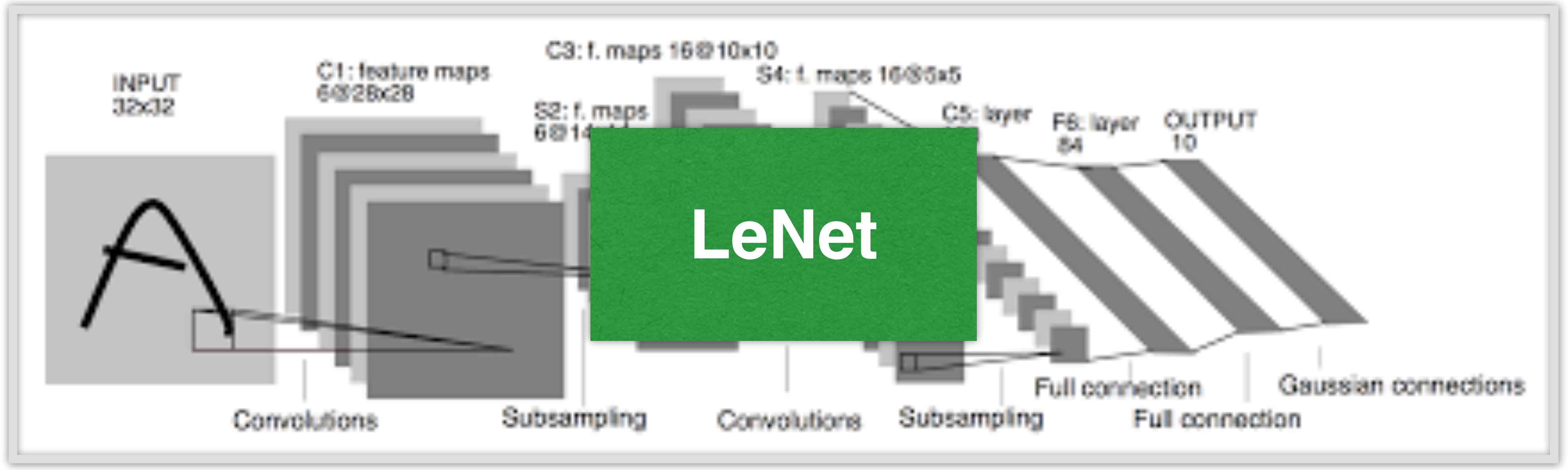
3*1 + 3*2 + 1*2 + 2*1 = 13

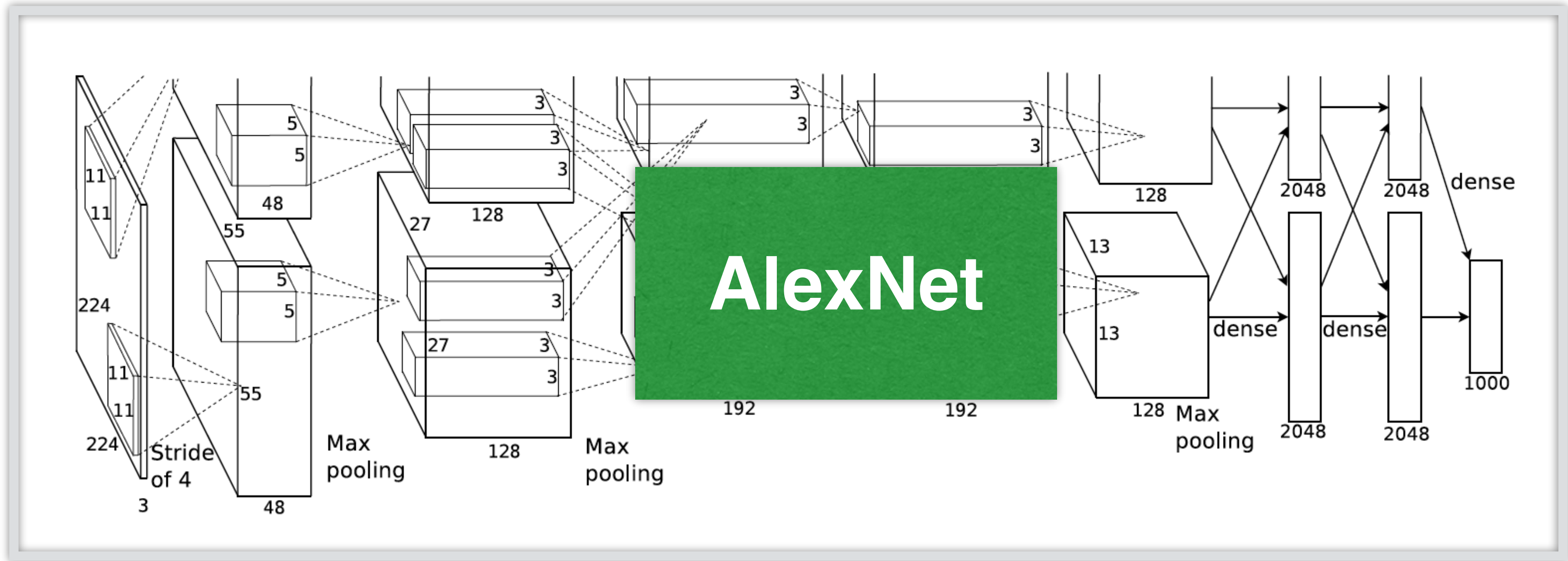
3*1 + 1*2 + 2*2 + 1*1 = 10

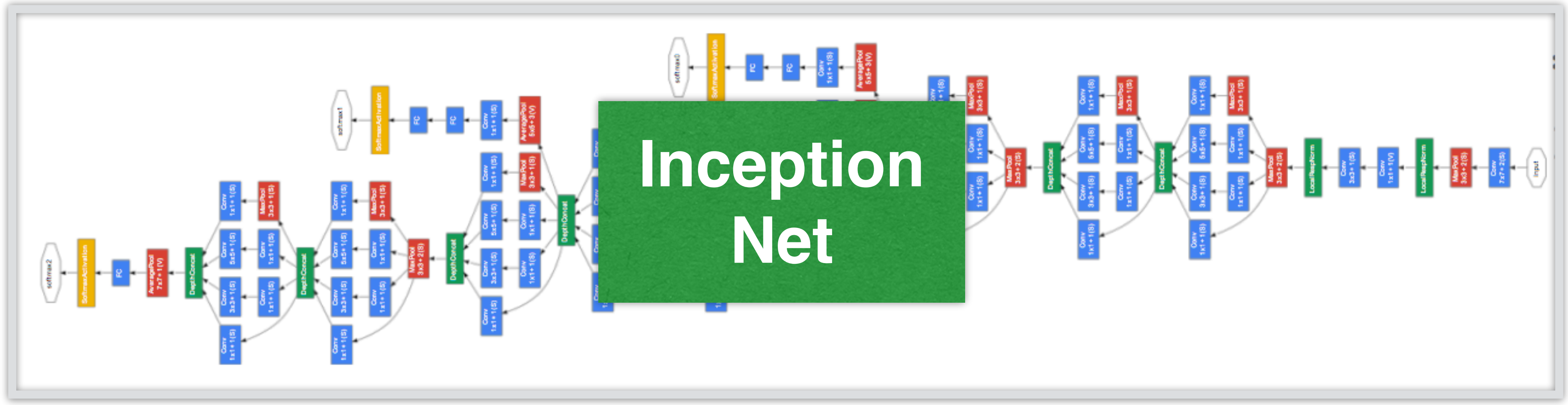
| | |
|---|---|
| **16** | **11** |
| **13** | 10 |

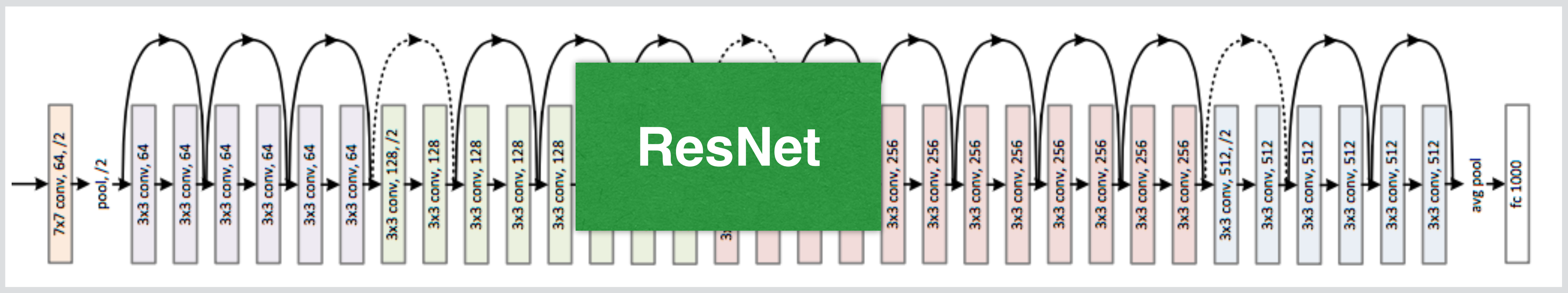
# Evolution of neural net architectures

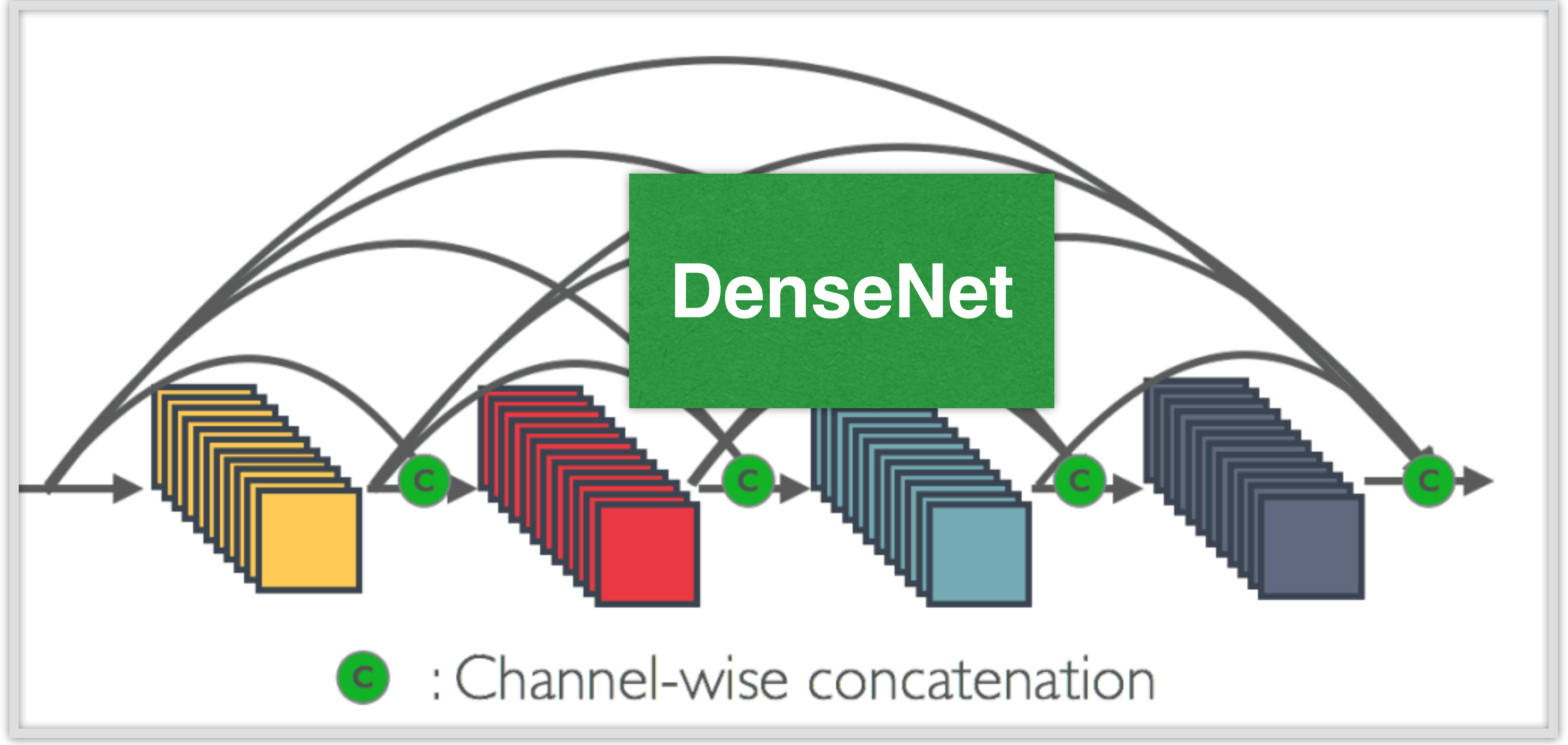
# Evolution of neural net architectures



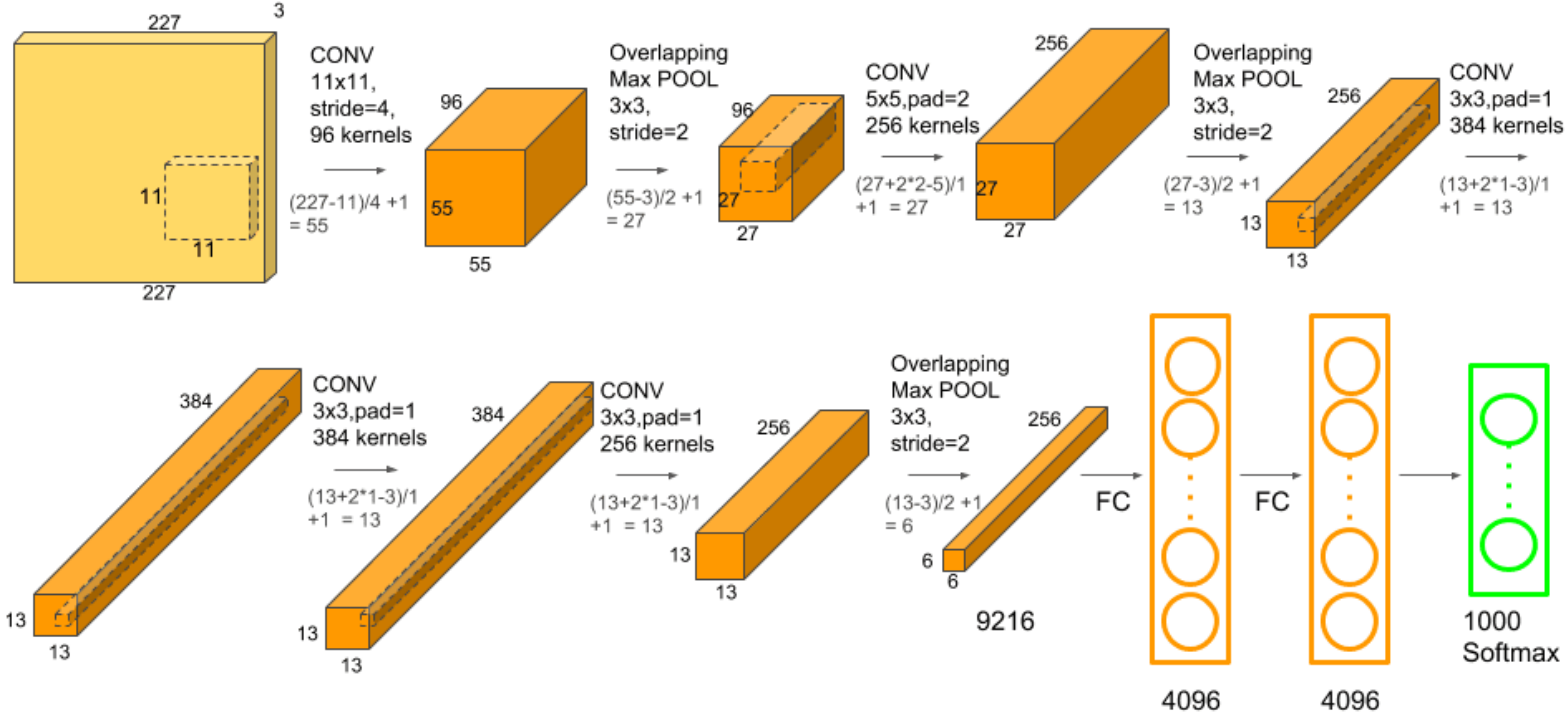



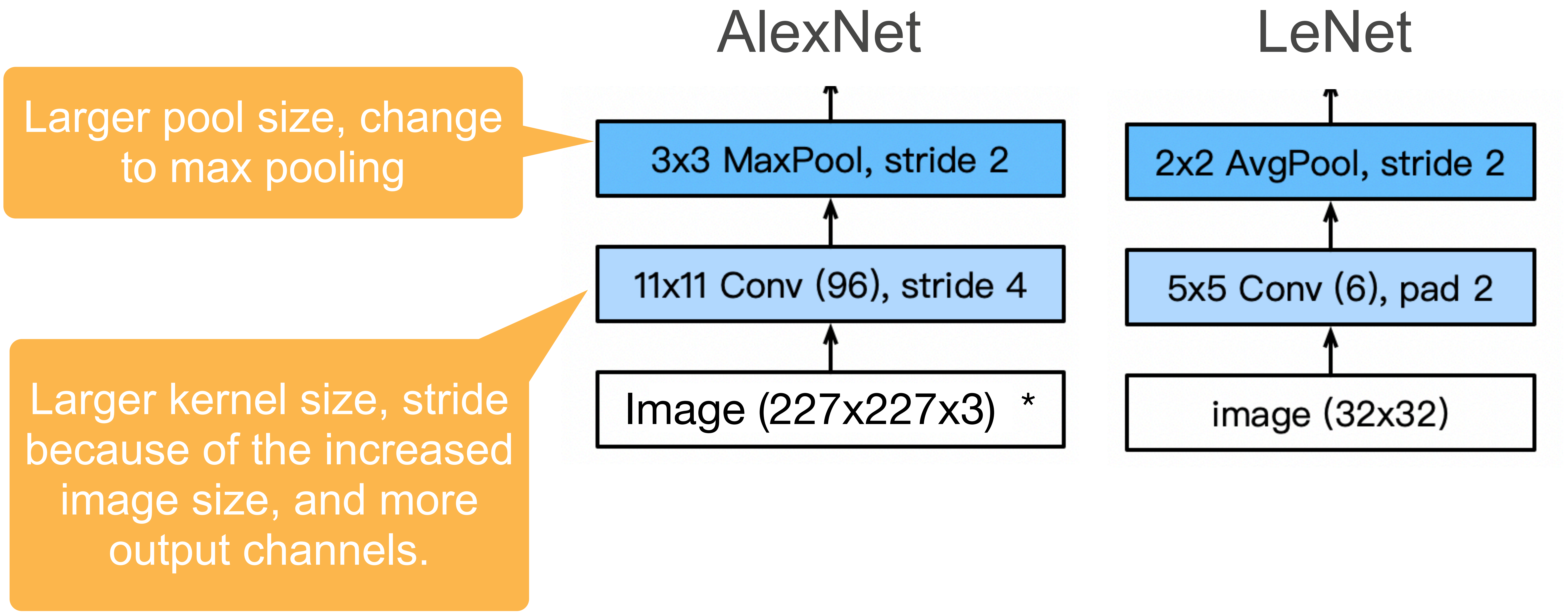

Deng et al. 2009

# AlexNet



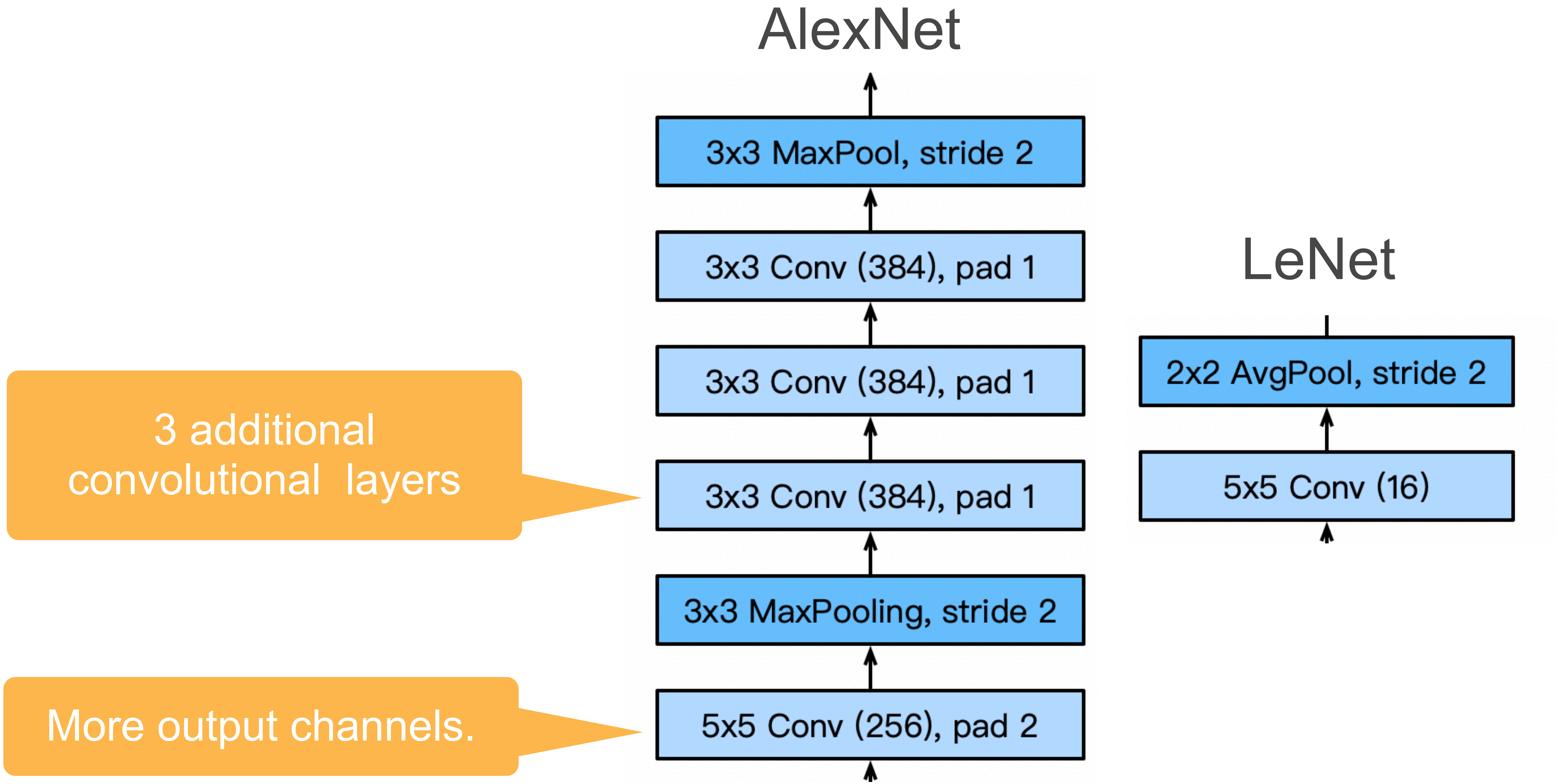

[Krizhevsky et al. 2012]

# AlexNet vs LeNet Architecture

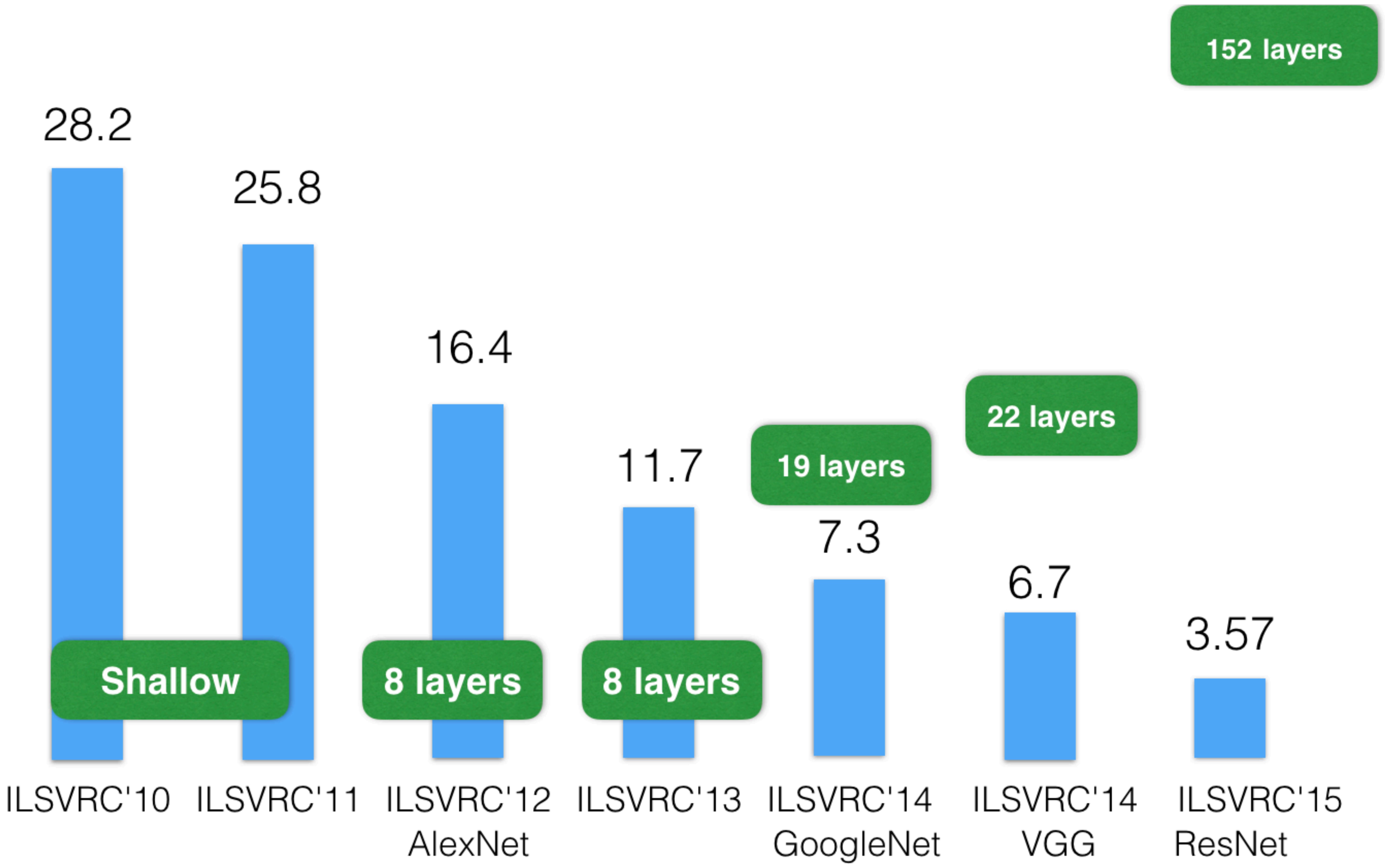



*Note that the original paper used 224x224x3, which was incorrect

# AlexNet Architecture



# **ResNet**: Going deeper in depth

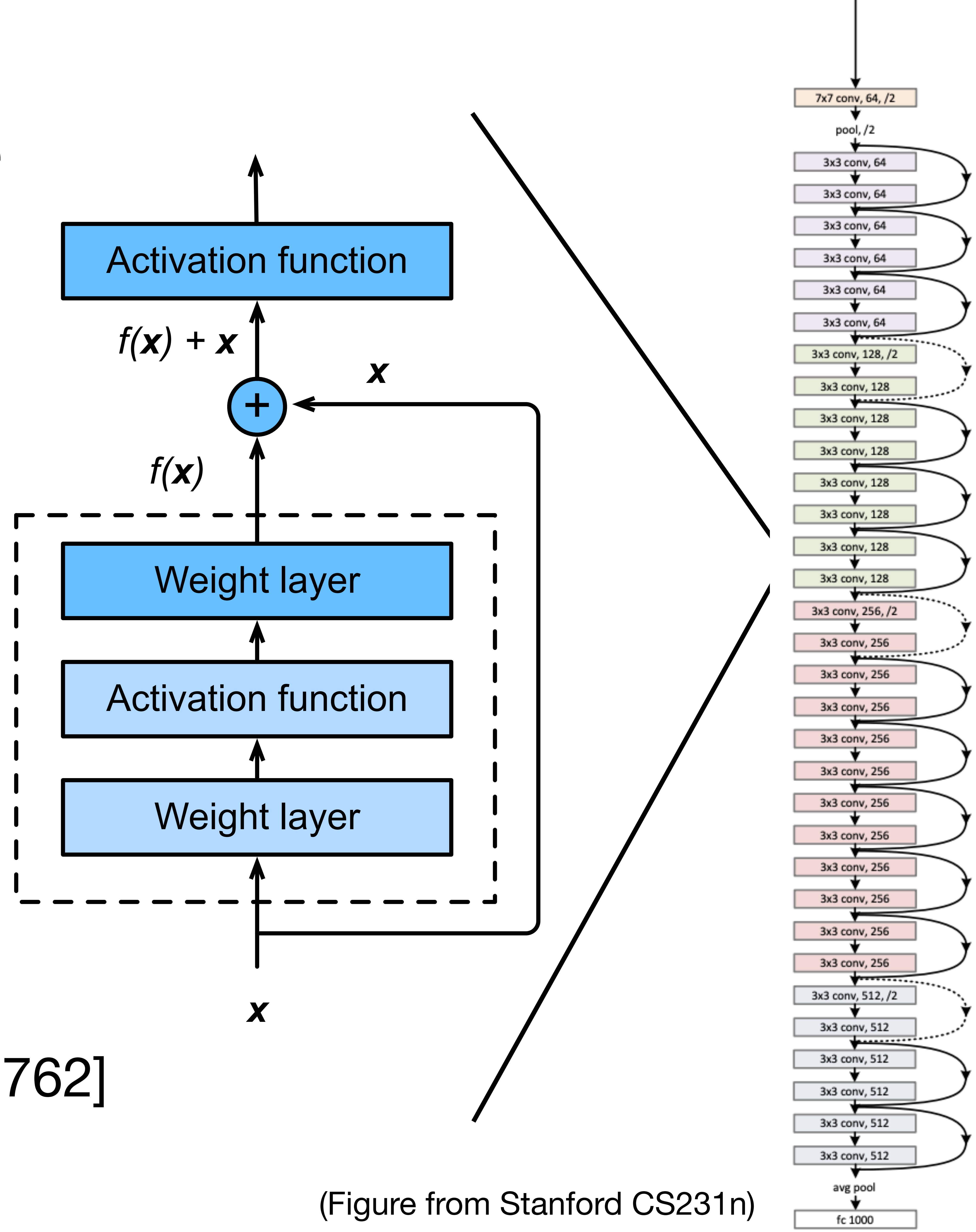



ImageNet Top-5 error%

[He et al. 2015]

# Full ResNet Architecture

## [He et al. 2015]



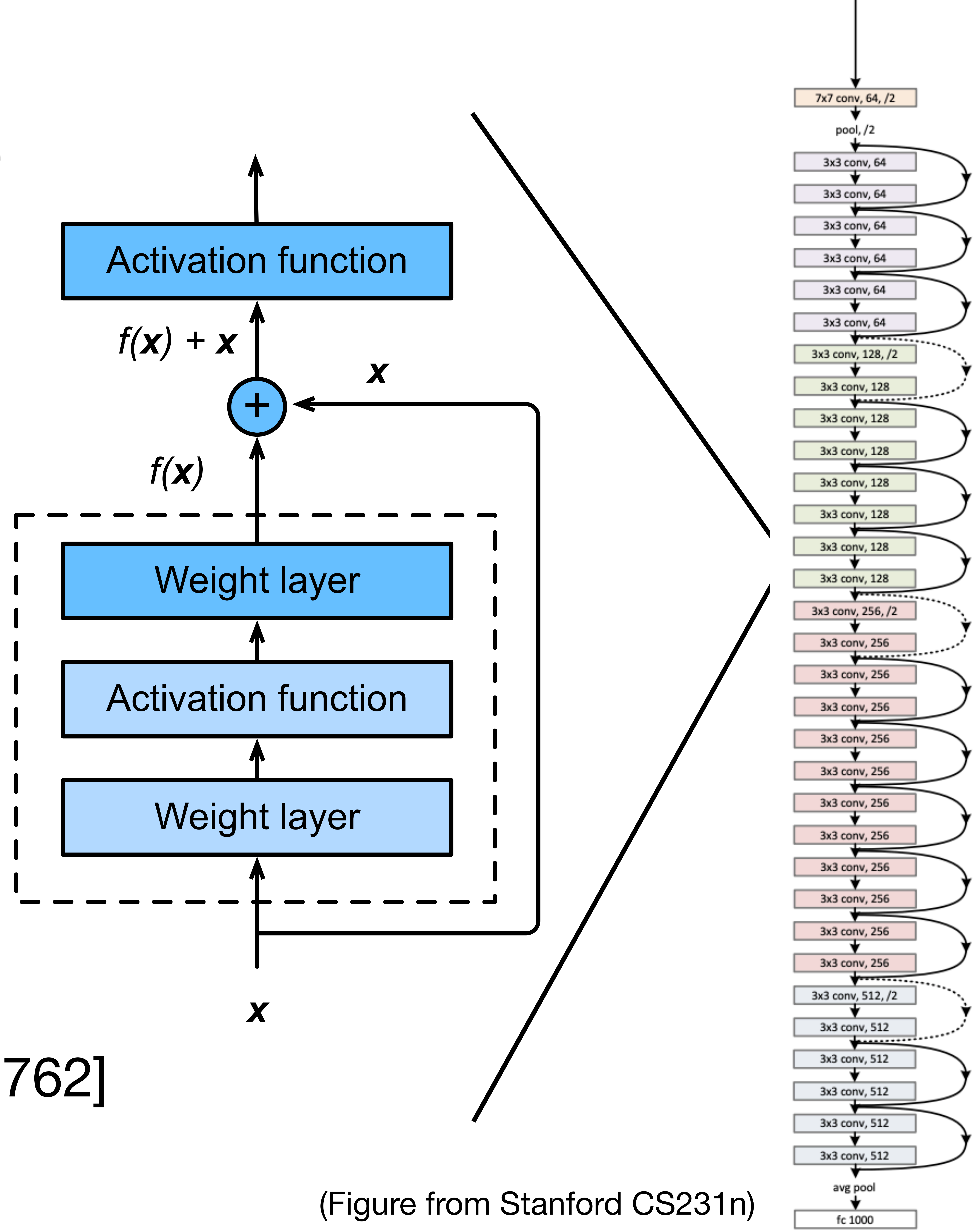

[More advanced topics covered in CS762]

(Figure from Stanford CS231n)

# Full ResNet Architecture

**[He et al. 2015]**

- Stack residual blocks



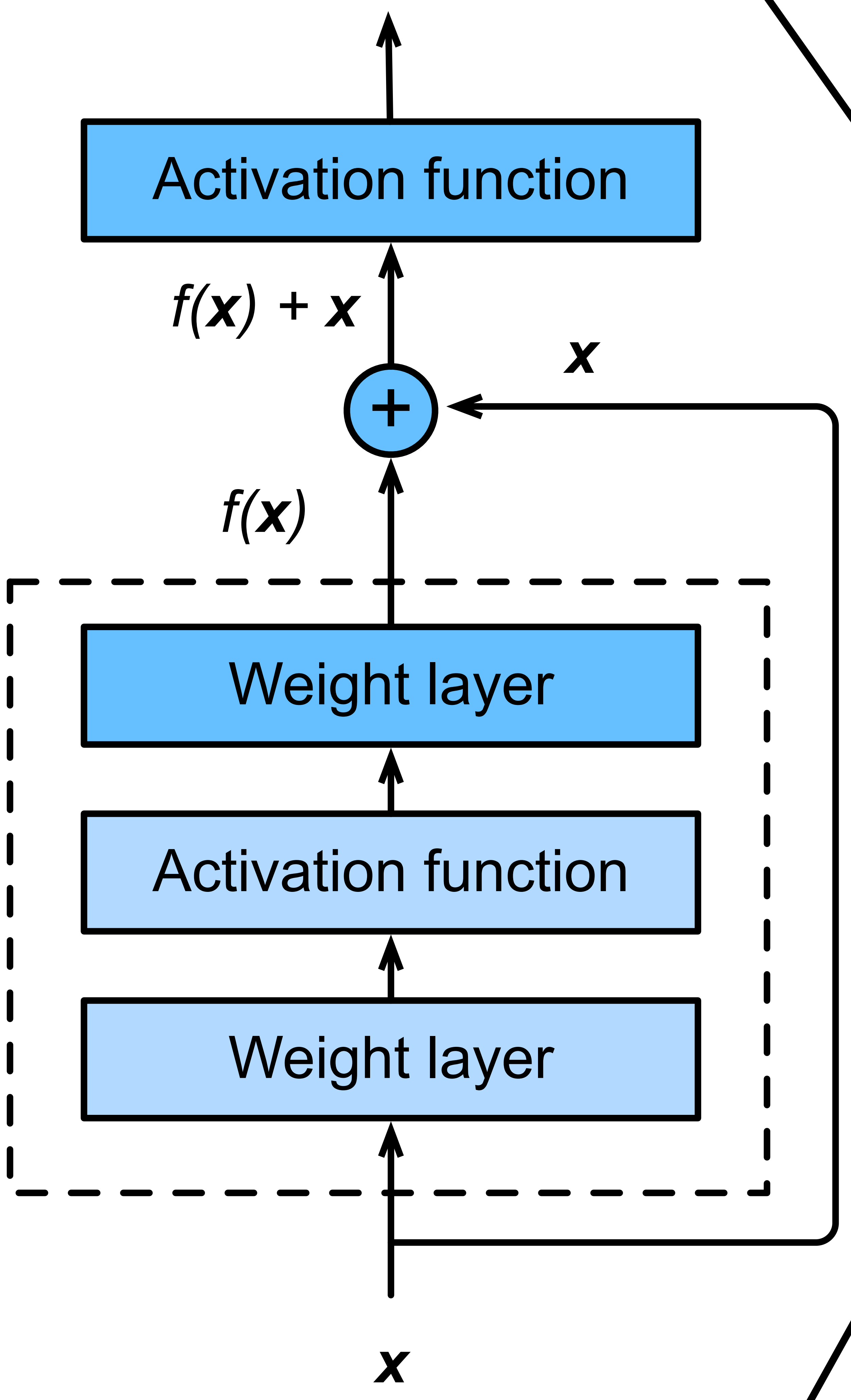

[More advanced topics covered in CS762]

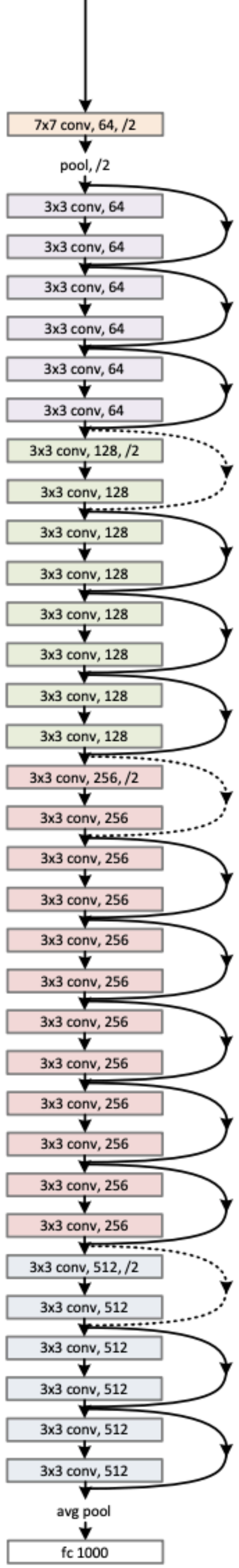
(Figure from Stanford CS231n)

# Full ResNet Architecture

## [He et al. 2015]

- Stack residual blocks
- Every residual block has two 3x3 conv layers




(Figure from Stanford CS231n)

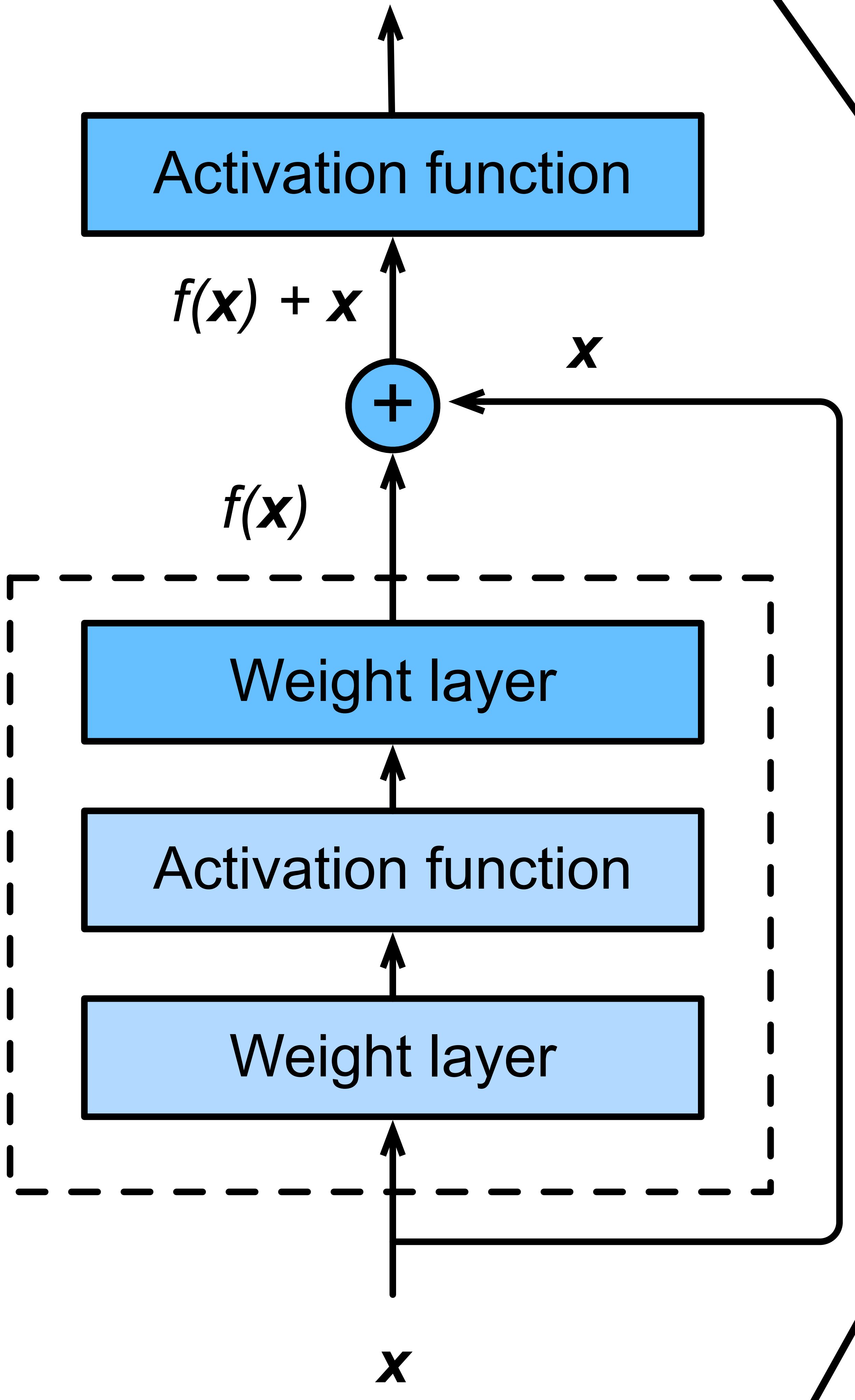
[More advanced topics covered in CS762]

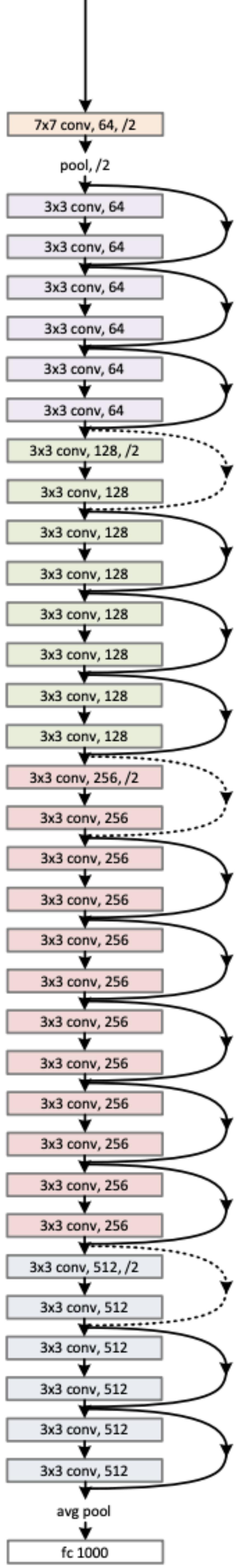
# Full ResNet Architecture

**[He et al. 2015]**

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride of 2 (/2 in each dimension)

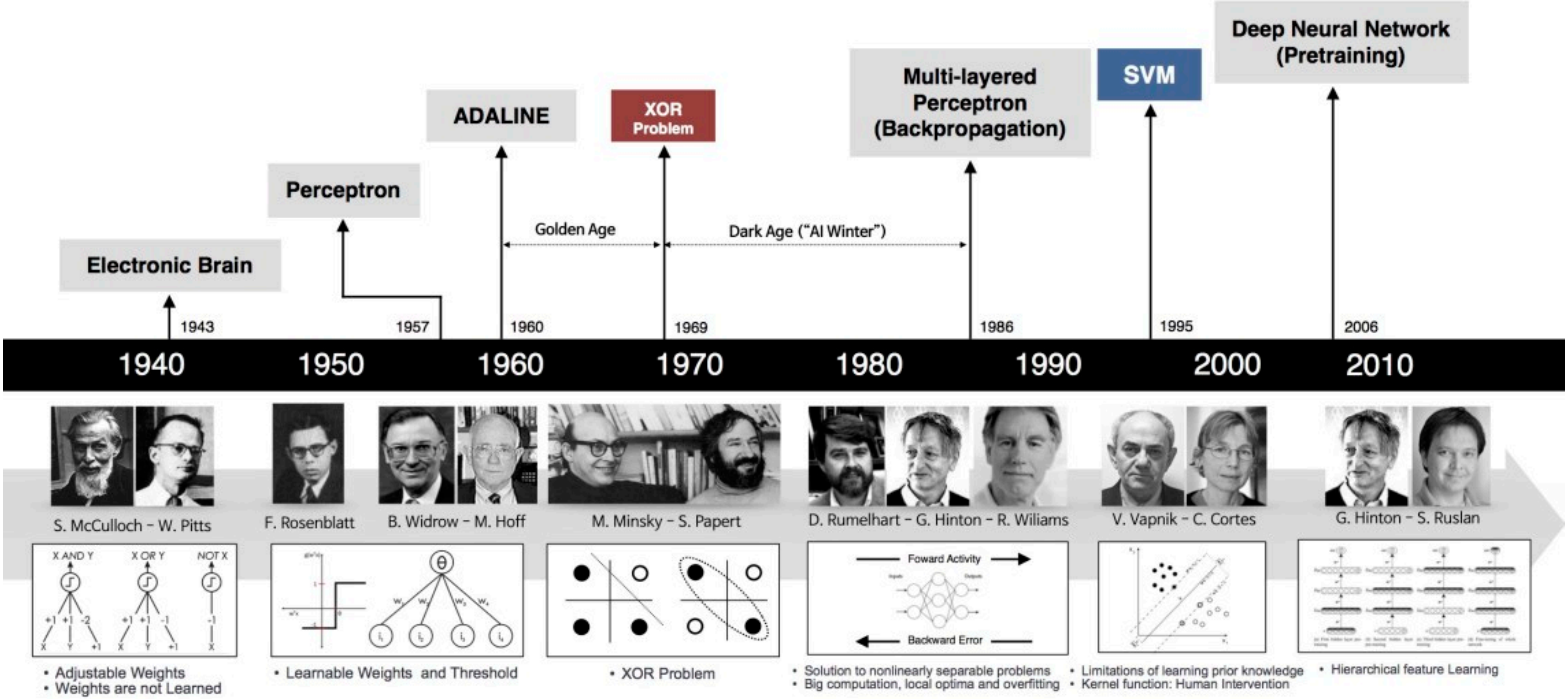
[More advanced topics covered in CS762]




(Figure from Stanford CS231n)

# Brief history of neural networks



# What we’ve learned today…

# What we've learned today…

- Modeling a single neuron

# What we’ve learned today…

- Modeling a single neuron
    - Linear perceptron

# What we’ve learned today…

- Modeling a single neuron
  - Linear perceptron
  - Limited power of a single neuron

# What we’ve learned today…

- Modeling a single neuron
  - Linear perceptron
  - Limited power of a single neuron
- Multi-layer perceptron

# What we've learned today…

- Modeling a single neuron
    - Linear perceptron
    - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks

# What we’ve learned today…

- Modeling a single neuron
    - Linear perceptron
    - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks
    - Loss function (cross entropy)

# What we've learned today…

- Modeling a single neuron
    - Linear perceptron
    - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks
    - Loss function (cross entropy)
    - Backpropagation and SGD

# What we've learned today…

- Modeling a single neuron
  - Linear perceptron
  - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks
  - Loss function (cross entropy)
  - Backpropagation and SGD
- Convolutional neural networks

# What we’ve learned today…

- Modeling a single neuron
    - Linear perceptron
    - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks
    - Loss function (cross entropy)
    - Backpropagation and SGD
- Convolutional neural networks
    - Convolution, pooling, stride, padding

# What we've learned today…

- Modeling a single neuron
  - Linear perceptron
  - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks
  - Loss function (cross entropy)
  - Backpropagation and SGD
- Convolutional neural networks
  - Convolution, pooling, stride, padding
  - Basic architectures (LeNet etc.)

# What we've learned today…

- Modeling a single neuron
  - Linear perceptron
  - Limited power of a single neuron
- Multi-layer perceptron
- Training of neural networks
  - Loss function (cross entropy)
  - Backpropagation and SGD
- Convolutional neural networks
  - Convolution, pooling, stride, padding
  - Basic architectures (LeNet etc.)
  - More advanced architectures (AlexNet, ResNet etc)

# Thank you!

Some of the slides in these lectures have been adapted from materials developed by Alex Smola and Mu Li:
https://courses.d2l.ai/berkeley-stat-157/index.html